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# How Advice and Its Source Characteristics Prompts Changes in Investment Decisions

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## Abstract

*People are using the Internet for financial planning assistance. Yet those seeking advice on the Internet rarely tend to question the advice source. Little research has examined the unique aspects of online financial advice taking. Online advice offers a unique setting which does not mirror “offline advice”. This paper addresses the research questions (1) What kinds of people are more likely to change their investment decisions given different online source characteristics, (2) How do people change their investment decisions given the disclosure of human vs. computer advice sources, and (3) How do people change their investment decisions given the disclosure of source credibility? This study finds that users with higher levels of task-specific self-efficacy are less likely to take advice and certain online design features influence changes in investment advice taking.*

*Keywords: Advice taking, source characteristics, source credibility, human vs. computer sources, online investing, laboratory study.*

## Introduction

People are turning more and more to the Internet for financial planning assistance, with 81% of these people specifically seeking advice about their investment choices (Madden and Rainie 2003). Yet many of the web sites providing investment advice do not provide warnings about the appropriate use of the information they offer and they fail to disclose the authority and qualifications of the advice source (Stanford et al. 2002). Furthermore, those seeking advice on the Internet rarely tend to question the advice sources, as only one quarter of them are vigilant about verifying the information on the Internet, one quarter are concerned but do not verify the information they get, and about half simply rely on their own judgment and rarely check the source (Fox and Rainie 2002). To further complicate the situation, it is usually subject matter novices who are most likely to seek advice and they have been found to judge online information based on the web site’s visual design while subject matter experts assess the site’s source, motives and biases (Fogg et al. 2002; Stanford et al. 2002).

The popularity of using the Internet for investment advice has also attracted deceitful people who attempt to misuse investors' money. The Federal Trade Commission (FTC) and Securities and Exchange Commission (SEC) actively pursue internet fraud which continues to be problematic. For example, the SEC reports: "Matthew Bowin recruited investors for his company ... done entirely over the Internet. He raised \$190,000 from 150 investors. But instead of using the money to build the company, Bowin pocketed the proceeds and bought groceries and stereo equipment..." (Anonymous 2007). Even with the government attempting to police the Internet, online advice seekers must become more aware of the need to examine source characteristics of the advice.

When and why people take advice has been the subject of much research (Harvey et al. 2000; Yaniv 2004), however little has examined the unique aspects of online financial advice taking. Online advice offers a unique setting which does not mirror "offline advice" exactly, although some commonalities are likely shared. This paper examines online advice taking by focusing on the unique aspects of: the users where self-efficacy plays a role; different source types where humans or computer algorithms can be advice providers; and source credibility issues which may or may not be readily discernable in the online environment.

## Theoretical Background

This research examines how people take advice when source characteristics are not clear. We first examine two broad topics—the role of advice taking in general decision making and advice taking in an online decision making context.

### *Literature review*

*Advice taking.* To reduce uncertainty in decision making, people gather and combine information from different sources including the opinions of others (i.e., advice). People decide whether to use advice based on their beliefs about their own level of expertise, as well as their beliefs about the expertise of the advice source (Birbaum et al. 1976). Consistent with the advice taking literature, we use the term *weight* when describing advice taking. When people give less weight to advice, they discount the advice and do not incorporate it in their decisions. Studies show people weigh advice based on characteristics of their advisor and of themselves before deciding how to combine advice with their own opinions. Analysis shows (1) people tend to place more weight on their own opinion than an advisor's opinion, (2) experts discount advice more than non-experts, (3) people weigh advice less as the distance of the advice from their own opinion increases, and (4) people assess the weight to place on advice to improve their decisions but not to an optimal level (Yaniv 2004).

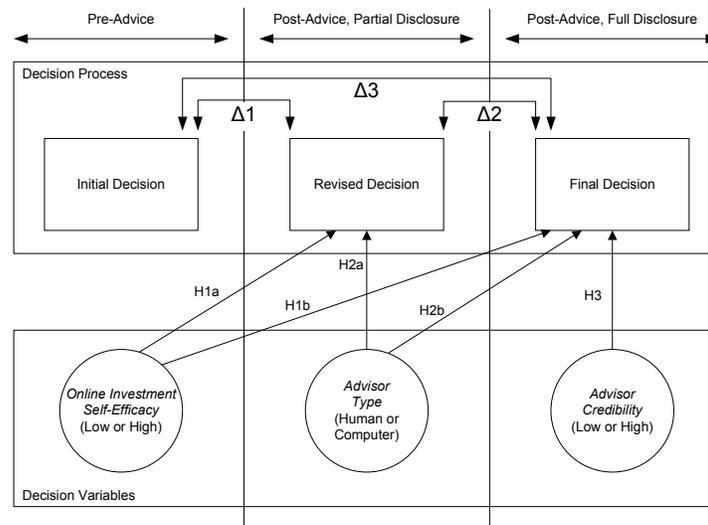
People may place greater weight on their own opinions than advice because they know their own reasoning but not the advisor's. Being more knowledgeable in a subject allows one to increase his/her reasoning even more. People seek out opinions of others when they have little experience in the topic. Advice that is near one's opinion may reinforce one's opinion, but advice far from one's opinion may suggest either one's opinion or the advice is a mistake (Yaniv 2004). Along this line, a person is less likely to take advice as the distance between his/her opinion and the advice grows greater. Extreme advice falls outside one's realm of acceptance and causes him/her to generate counter-arguments or disparage the advisor (Yaniv 2004). Reducing the distance leads people to incorporate the advice and to shift opinions to that of the advisor. Thus, people weigh advice depending on their own expertise, the advisor's expertise, and their own quality assessment of the advice.

*Online advice.* The online context is an appropriate domain in which to test advice taking because there are varying degrees of expertise by those seeking out advice, different types of advice such as human advisor and computerized algorithm sources, and different levels of advice credibility. The online experience differs from the equivalent face-to-face experience as Internet users must rely on limited representations such as graphics and text descriptions (i.e., the visual design). Web sites can mask deficiencies in the advice source or mislead users to believe that information they provide is reliable through well designed web pages and powerful web features (Koufaris 2002). Web designers, including those providing misleading information, follow specific guidelines to increase the confidence that users place on the information and advice provided. These guidelines include: seals of approval, justification of advice given, independent peer evaluations, alternative views, ease of use, a professional image, etc. (Schneiderman 2000). Yet these guidelines differ in how well they influence user confidence (Belanger et al. 2002; Gefen et al. 2003). Thus, web sites make discerning advice credibility more difficult than face-to-face exchanges of information.

People seek out advice from credible sources, but does this also hold for advice coming from computerized software that provides advice using neural network and software-driven models and algorithms (see [www.blackboxinvesting.com](http://www.blackboxinvesting.com))? Web sites can provide advice not only from human advisors offering investment suggestions but also from computerized algorithms and models using technical indicators to provide investment recommendations. Online investors must either decide to trust and follow the recommendations or to reject them. Research has shown auditors using computerized advice sources were better at determining management fraud risk and made more consistent decisions (Ashton 1992). Novices are more willing to rely on computer aids and achieve greater decision performance (Mackay and Elam 1992; Whitemcotton 1996). Finally, the design of the computerized interface has been shown to impact when and how people rely on the algorithm-based advice (i.e., rule-based, neural or Bayesian networks) (Silver 1991). Thus, people may use the source characteristics of online advice to determine how to weigh the advice in making their investment decisions.

**Research model**

The proposed research model (illustrated in Figure 1) investigates the manner in which online advice can influence decision making. The model is specifically designed to “open up the black box” of decision making (Mackay and Elam 1992), focusing on the processes and mechanisms that explain user behaviors without examining the performance outcomes of decision making.



**Figure 1. Research Model**

In the research model, user behavior is examined as the decision process consisting of three sequential decisions. First, users rely on their own ability to formulate an *initial decision*, which is made without the aid of advice (Pre-Advice) (Birnbaum et al. 1976; Yaniv 2004). Then, users seek advice and a *revised decision* is made (Harvey et al. 2000). To figure out how much to revise their decision, users assess their own opinion along with the advice given (Post-Advice, Partial Disclosure). On a web site, limited information about the sources’ characteristics may be available or that information may not be easily discernable (Gefen et al. 2003; Koufaris 2002). Regardless, users must decide how to incorporate the advice in their decisions. After making the revised decision, detailed information about the quality of the advice source is revealed which is consistent with users taking the time to seek out and inquire about the information source (Post-Advice, Full Disclosure). The decision makers make a *final decision* based upon information that has been fully disclosed about the advice source. Within the decision process steps, each decision is modeled as being effected by a succession of variables: one variable is related to the characteristics of the users and two are concerning the characteristics of the online advice.

*Online investment self-efficacy.* Because the initial decision is devoid of advice, users must rely on their own ability to make an effective decision, which will likely be influenced by the characteristics of the decision makers. Self-efficacy is defined as “people’s judgments of their capabilities to organize and execute courses of action required to attain designated types of performances” (Bandura 1986, p. 391). Self-efficacy plays a critical role when one interacts with technologies (Compeau and Higgins 1995; Marakas et al. 1998). The model includes the concept of online investment self-efficacy (OISE), which is defined as an individual’s perceived capability to utilize online investing technologies to make effective investing decisions. As such, OISE refers to an individual’s perceived ability to utilize online technologies to accomplish investing tasks (Looney

et al. 2006). Self-efficacy judgments pertain to the level of certainty that one can effectively accomplish a given task. Users possessing lower levels of self-efficacy should be less certain about their ability to perform and, thus, will be more likely to resolve uncertainty by relying on external advice. Those with higher levels of self-efficacy, in contrast, should be more certain about their ability to perform the task well on their own.

H1a: Post-Advice with Partial Disclosure, users with lower levels of OISE will weigh online advice significantly more than those with higher levels of OISE.

H1b: Post-Advice with Full Disclosure, users with lower levels of OISE will weigh online advice significantly more than those with higher levels of OISE.

*Advisor type.* The remaining variables focus on the characteristics of the online advice source. In the revised decision, advisor type (ATYPE) is introduced as the mechanism for partial disclosure. ATYPE refers to whether the advisor is a human being or computer algorithm. The revised decision is based upon the effects of OISE and ATYPE. People tend to trust other individuals because others have different life experiences and expertise, their perspective is based on sentient intellectual resources, and others are perceived to know what is going on (Fogg 2003; Reeves and Nass 2002; Tseng and Fogg 1999). Meanwhile, people tend to distrust computerized black box advice, which are perceived to be only as good as the models, algorithms or formulae upon which the advice is based (Fogg 2003; Reeves and Nass 2002). However, people tend to attribute human characteristics to technology objects or they perceive some human properties in these objects during their interactions with the technology (Reeves and Nass 2002). Some would argue that people treat computers as social actors, apply social rules to them, and use words like “integrity,” “honesty,” “cruelty,” and “harm” to characterize technology behavior (Wang and Benbasat 2005). People respond socially to technology and perceive that they possess human characteristics. But most importantly, research shows that the trust people place in other humans and in technology artifacts do not differ significantly (Jain et al. 2000). People not only utilize computer as tools but also from relationships with them. Thus, we expect users to take advice just as often from a human advisor source as from a computerized algorithm source.

H2a: Post-Advice with Partial Disclosure, users with ATYPE human advisors will weigh online advice similarly to than those with ATYPE computer algorithms.

H2b: Post-Advice with Full Disclosure, users with ATYPE human advisors will weigh online advice similarly to than those with ATYPE computer algorithms.

*Advisor credibility.* Advice credibility (ACRED) is introduced before the final decision. ACRED refers to whether the advisor is trustworthy and possesses expertise. Thus, decision makers base their final decision on OISE and the full disclosure of advice source characteristics (ATYPE and ACRED). Some online investment web sites provide users with advice credibility indicators—additional information beyond the advice to guide decisions on how much weight to place on the advice. Credibility indicators indicate the validity of the advice and its source. From an advice taking perspective, credibility indicators may encourage users to continue moving toward (i.e., place greater weight on) or moving away from (i.e., place less weight on) the advice provided. Unexpected inaccuracies in the advice may raise doubts about the advice’s validity (Sedlmeier and Gigerenzer 2000), and online investors may turn to credibility indicators to determine advice validity and to substantiate the weight they should place on the advice (Melnik and Alm 2002). We expect credibility indicators to influence the manner in which advice validity influences the weight users place on advice provided. Strong (high) credibility indicators give users a reason to believe that advice is valid and encourages them to place greater weight on the advice—that is, they are encouraged to discount their own opinions in favor of the advice provided.

H3: Post-Advice with Full Disclosure, users with high ACRED will weigh online advice significantly more than those with low ACRED.

In Figure 1, shifts among the decision points are represent by the  $\Delta$ s among initial, revised, and final decisions. Although there are three shifts that could potential be examined,  $\Delta 1$  between the initial and revised decision,  $\Delta 2$  between the revised and final decisions, and  $\Delta 3$  between the initial and final decisions—the primary purpose of the model is to understand the processes by which online advice affects user behaviors. Consequently this study focuses on  $\Delta 1$  and  $\Delta 2$ .

## Methodology

### *Subjects and task*

This study involved 429 undergraduates enrolled in business courses at three large universities. This sample was purposefully chosen. First, since the experimental design required the manipulation of online investment self-efficacy,

inexperienced online investors were sought. Self-efficacy judgments tend to be more malleable given an absence of relevant experiences (Gist and Mitchell 1992). As such, self-efficacy beliefs of inexperienced individuals are more easily modifiable, facilitating a strong test of the theory. Second, the majority of online investors tend to be computer-savvy (Barber and Odean 2001). Varying degrees of computing skills could plausibly contaminate results. Novice computer users devote substantial effort and attention to interacting with the computer rather than focusing on the task (Mackay and Elam 1992). By pre-selecting computer-savvy people, we control for this potentially confounding effect. Finally, this study measures the change in decisions based on different levels of advice provided and not the ability of decision making based on investment performance information. Student subjects may lack the experience needed to reach optimal investment decisions, however, this is not relevant to the study. Relevant to the study is how subjects change their decisions based on the advice provided.

Subjects received course credit for their participation and were eligible to earn a prize based on their performance. All experimental sessions were held in campus computer labs. First, subjects completed a pretest on demographics and prior experience with investment decisions. Subjects were randomly assigned to one experimental manipulation. Next, they performed two training exercises, which also manipulated their OISE level by either praising them for excellent performance or notifying them of unsatisfactory performance. The experiment asked subjects to allocate \$100,000 to two different stocks, called generic names A and B in order to reduce any effects of preconceived bias based on actual company names, in a simulated online investment environment. Subjects were told the average investor would invest \$50,000 in each of the stocks and that their decision quality would be judged against how well their investments performed versus the average investor for a three month post-decision period.<sup>1</sup>

Subjects were asked for their initial investment allocations. Up to this point, subjects were not told they would be receiving advice. When they received the advice, it was the first time they thought about whether to incorporate it into their decisions. If they knew that advice would be provided, subjects may have made different pre-advice allocation decisions. Subjects were provided advice on how to make their allocations which unknown to subjects always suggested an opposite investment allocation to the one they initially selected.<sup>2</sup> All subjects were provided with information about whether their advice came from a human advisor or computer algorithm at the *revised decision* step, and the credibility of their advice source at the *final decision* step. They were given the chance to update their investment allocations. The task was designed to capture three allocation values: (1) before receiving advice, (2) after advice with the partial disclosure of source type and (3) after advice with the partial disclosure of source credibility were disclosed. As such, the change in investment allocations could be assessed to objectively measure how heavily the subject weighed the advice. Subjects then answered manipulation check and post-task questions.

### ***Independent variables***

Three variables were manipulated in this study: OISE, ATYPE and ACRED. OISE was manipulated by indicating the participant's performance on two practice exercises. Colorful statements either praising them for excellent performance (high) or notifying them of unsatisfactory performance (low) were provided. ATYPE was manipulated by a picture and statement regarding whether the advice source was a computerized algorithm or a human advisor. ACRED was manipulated through statements about whether the advice source was highly trustworthy with high expertise (high) or not trustworthy with little expertise (low). Subjects saw only the information pertaining to the treatments they were assigned.

### ***Dependent variable***

Three dependent variables were examined regarding online advice taking. The dependent variables reflect the investment allocation changes between the three decisions made: initial, revised, and final. More specifically, following Yaniv and Kleinberger (2000) and Yaniv (2004), online advice taking was calculated by the difference between the initial amount allocated to the first stock (i.e., pre-advice) and the amount allocated to the first stock after the advice was provided (initial decision) to test H1a and H2a. Then online advice taking was calculated by the difference between the amount allocated to the first stock after the advice was provided (initial decision) and the amount allocated to the first stock after the source type was disclosed (revised decision) to test H1b, H2b, and H3. These differences were divided by the total possible allocation

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<sup>1</sup> The program would not allow a \$50,000 allocation to each stock since the intent was to get commitment to one stock over the other. The program would also not allow allocations that did not total \$100,000.

<sup>2</sup> Advice suggested an allocation opposite the subject's allocation by \$50,000. If a subject initially allocated \$30,000 to stock A and \$70,000 to B, the advice suggested allocating \$80,000 to stock A and \$20,000 to B.

change of \$50,000 to calculate the amount of weight placed on the advice, ranging from 0 (advice was not taken) to 1 (advice was completely followed).<sup>3</sup>

## Results

### *Manipulation checks*

Prior to testing the hypotheses, manipulation checks were analyzed to confirm the effectiveness of experimental treatments. To confirm the manipulations, ANOVAs were conducted using the treatment groups as independent variables and the manipulation check item scores (i.e., summated for multiple items) as the dependent variables. As expected, a significant difference in OISE scores emerged between the self-efficacy treatment groups,  $F(1,418)=133.609, p<0.001$ . A significant difference emerged regarding ATYPE across source type treatment groups,  $F(1,418)=289.107, p<0.001$ . ACRED manipulation check was also significant across credibility treatment groups,  $F(1,418)=257.945, p<0.001$ . No unexpected patterns across groups or interaction effects were significant. Subjects in different treatments perceived differences as anticipated.

### *Hypothesis testing*

Hypothesis 1a and 1b proposed that users with lower levels of OISE would weigh online advice significantly more than those with higher levels of OISE. As anticipated, self-doubting users placed significantly more weight on the advice ( $M=.51$ ) than those who deemed themselves as capable online investors ( $M=.31$ ) at the revised decision step,  $F(1,424)=26.371, p<0.001$ . They also placed significantly more weight on the advice ( $M=.37$ ) than those who deemed capable ( $M=.26$ ) at the final decision step,  $F(1,424)=6.113, p=0.01$ . Hypotheses H1a and H1b were supported. Hypothesis 2a and 2b suggested that users would weigh online advice from a human source similar to a computer source. Those receiving online advice from a human advisor did not weigh the advice more heavily ( $M=.42$ ) than those receiving advice from a computer algorithm ( $M=.39$ ) at the revised decision,  $F(1,424)<1, ns$ . Those getting advice from a human ( $M=.33$ ) also did not weight the advice differently than those receiving it from a computer ( $M=.30$ ) at the final decision step,  $F(1,424)<1, ns$ . Hypothesis H2a and 2b were supported. Hypothesis 3 projected that users would weigh online advice from a source that is perceived as higher in credibility significantly more than a source that is perceived as lower in credibility. Those receiving advice from a more credible source ( $M=.54$ ) weighed online advice significantly more than those receiving advice from a less credible source ( $M=.09$ ) at the final decision step,  $F(1,424)=140.255, p<0.001$ . Hypothesis H3 was supported.

## Discussion

The purpose of this study was to examine how online design features and user characteristics influence reliance on online advice. This study found that users with higher levels of task-specific self-efficacy are less likely to take advice for their revised and final decisions. That is, they are less likely to incorporate the advice in their decision making and they tend to place less weight on the advice than their own opinions. Given these findings, task-specific self-efficacy should be regarded as a critical variable to include in similar future studies. Online design features were also shown to influence advice taking. High source credibility led to greater advice taking in final decisions and source credibility appears to matter even when users have certainty in their own capability (i.e., high task-specific self-efficacy) to make a decision. This study illustrates the importance of disclosing credibility information to all users. Finally, advice source type had little influence on users in the context of this study in either the revised or final decisions suggesting then need for future research.

To further analyze the findings, Figure 2 provides the means of the actual dollars allocated for one stock for each treatment cell across the initial, revised, and final decisions made. One finding of particular interest is that those with low self-efficacy ( $M=-.44$ ) reacted more after full disclosure of low source credibility than those with high self-efficacy ( $M=-.17$ ),  $F(1,210)=23.073, p<0.001$ . This finding was not found after full disclosure suggested the source had high credibility, where those with low self-efficacy ( $M=.15$ ), reacted similar to those with high self-efficacy ( $M=.08$ ),  $F(1,212)<1.8, ns$ . This finding is consistent with prospect theory, which describes how people make choices in situations where they have to decide between alternatives that involve risk, e.g. in financial decisions. The theory describes how individuals evaluate potential

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<sup>3</sup> Allocations for the second stock were not needed since they mirrored allocations to the first stock.

losses and gains and suggests when people exhibit risk-averse behavior (Kahneman and Tversky 1979). Because low source credibility reflects more negative information, this may signal to users that there is a greater probability of losses. Future research is needed to clarify how self-efficacy and investment gains and losses interact.

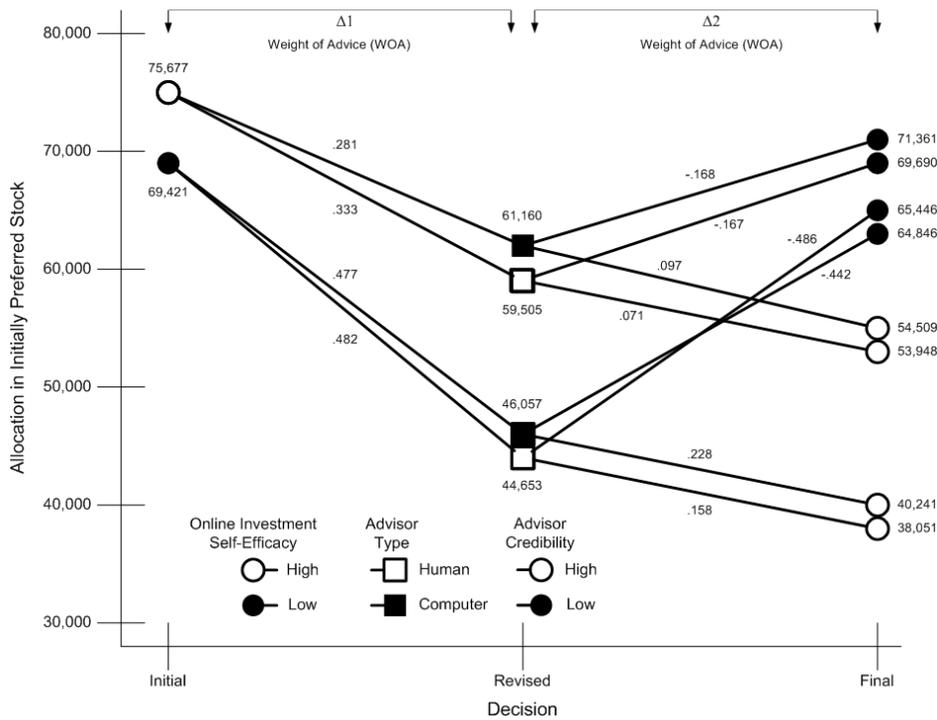


Figure 2. Results

The findings from any study must be assessed in light of the study's limitations. For this study, the increased control afforded by a laboratory experiment must be traded off against the inherent limitations of the approach, primarily that of generalizability. The use of student subjects, the nature of the tasks, and the operationalization of the advice, online investment self-efficacy, online advice source type and online advice credibility all limit the generalizability of our results. To adequately test the research model, we needed to manipulate OISE as well as find subjects that were computer-savvy. Thus, this study required a subject pool of inexperienced investors having computer skills, which lead to the selection of student subjects (Beltramini 1983; Morgan 1979). We might not have been able to test the theory if our subject pool comprised experienced online investors because the manipulation of OISE probably would not have been as successful. Our subjects had experience using web-based applications and hands-on experience from two practice sessions with the online environment used in the study. Thus, they understood the context and the task. Subjects were offered course credit and prize incentives to increase their motivation to perform well. Regardless, research using non-student samples is warranted.

The task involved allocating investment dollars to two pre-selected stocks which may limit the generalizability of these findings to tasks involving advice in similar settings. However, there are many domains in which Internet users may need to decide whether to discount advice. The operationalizations of the independent variables were considered a strength of this study due to the tight controls implemented. In real-life situations, users would more likely be faced with a mix of information—and future research should investigate the role of mixing types of information.

A major contribution of this study was that online advice is not ignored but matters in decision making, especially when investors have low task-specific self-efficacy and the advice is highly credible. More research is needed to test additional theories for why users take advice in online settings. For example, research could examine how prospect theory informs when people experience loss aversion and are more sensitive to decreases in their wealth than to increases. Thus, contexts differing on gains versus losses may influence how people take advice.

Advice taking can be a form of knowledge transfer where the knowledge on a certain topic from a more expert person is shared and provided to a less expert person (i.e., the advice seeker) (Huber 2001; Menon and Pfeffer 2003). Online knowledge repositories, bulletin boards, discussion boards, email threads and other electronic forms of knowledge documentation are becoming ubiquitous both within organizations and on the Internet. The results of this study suggest the

need to explore how users of these knowledge-based systems use the knowledge (i.e., advice) provided and its source characteristics in making efficient and effective decisions across multiple contexts.

Online brokerage firms, who are known to be lacking in terms of advice compared to full-service firms (Looney and Chatterjee 2002), would be well-advised to craft marketing messages targeted at efficacious individuals. Supporting this notion, one online brokerage firm recently launched an advertising campaign embracing the slogan "You're in Control," which captures the essence of online investment self-efficacy. Even individuals with higher OISE tend not to be completely certain, meaning that these individuals will also take some advice, albeit to a lesser extent than individuals with lower OISE. For these individuals to resolve uncertainty further, brokerage firms should incorporate advice clearly into their systems or provide alternative means for getting advice including gaining access to a human advisor.

Prevailing trends make it increasingly important to gain a deeper understanding of how advice can be provided to investors via web-based systems. A growing number of employer-sponsored retirement plans can now be managed by employees directly. Recent debate has surfaced concerning the possible privatization of the U.S. Social Security System, which would likely involve online components. The evidence, however, indicates that certain individuals may not be completely comfortable managing their money online. Consequently, it is critical that systems be designed to provide effective advice and credibility information so users can make informed investment decisions.

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