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2005

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ABSTRACT

The Internet offers limitless advice on a multitude of products and services. The quality of the advice varies and is inherently a matter of human judgment. To help users determine the quality of advice and whether to use the advice, design features of web sites include information about the type and credibility of the advice source. This research examines how characteristics of the online user (i.e., self-efficacy) and characteristics of the advice source (i.e., type and credibility) affect advice taking in an online investing context. A laboratory experiment provides evidence that users with higher levels of self-efficacy are less likely to take advice than those with lower levels of self-efficacy. Results also suggest users given highly credible advice are more likely to take the advice compared to users who receive advice with dubious credibility. The implications are discussed.

Keywords

Self-efficacy, Source credibility, Human-computer interaction, Online advice taking.

INTRODUCTION

Most decisions involve incomplete information about alternatives and outcomes. Seeking advice is one way that individuals reduce uncertainty when making decisions (Sniezak and Van Swol, 2001). People seek advice from those they trust or know to be experienced. People gather information and advice until the cost of doing so outweighs the benefits of making a decision based on the information and advice obtained. Today, the Internet offers a low-cost channel for users to get advice on a seemingly limitless range of topics.

Online advice is important in many contexts such as medical, religious, consumer purchasing, etc. In fact, 73 million people use online medical advice, 35 million seek online religious advice, and 21 million people use online financial advice (Fox and Rainie, 2002). People seek advice from the Internet to browse and learn new things, to collect information for future decisions, or to find quick and accurate input for immediate decisions. Regardless of the motive, people desire good advice and determining when it is accurate can be challenging.

Online advice is diverse and growing. Yet, an alarming number of web sites do not provide warnings about the use of the information they offer and many sites fail to give the qualifications of their sources. Less than half of medical information available online has been reviewed by doctors (Fox and Rainie, 2002). In one study, only 25% of users seeking advice on the Internet were vigilant about verifying the information, 25% were concerned but did not verify it, and roughly 50% said they relied on their own common sense rarely questioning the source (Fox and Rainie, 2002). Furthermore, experts and novices differ in their approach to assessing quality. Novices judge advice quality based on a web site's visual design while experts assess a web site's sources, motives and biases.

How and why people take advice has been the subject of much research (Harvey et al., 2000). However, little research has examined the unique aspects of online advice taking. Online advice differs from its offline counterpart because truthful and honest characteristics of the source cannot be as easily conveyed through the electronic channel. When searching for the same information offline, these issues are mitigated as face-to-face meetings allow the ability to read non-verbal cues of honesty, the ability to build a reputation over repeated interactions, and a more costly setting for reaching millions of people. Given concerns over the reliability of online advice, this research investigates how design features and user characteristics influence reliance on online advice in an immediate decision making context.

LITERATURE REVIEW

Advice Taking

To reduce uncertainty in decision making, people gather information from different sources including others' opinions. To maintain consistency 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. Analysis shows (1) people place more weight on their own opinion than an advisor's, (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 decisions but not optimally (Yaniv, 2004).

People place greater weight on their own opinions versus advice because they know their own reasoning but not the advisor's (Yaniv, 2004). Being more knowledgeable in a subject allows one to increase his/her reasoning even more. Thus, people seek out opinions of others when they

have little experience in the topic suggesting characteristics of the person may influence advice taking.

People are found to make a final decision by combining their own opinion with the advice given. They may determine how much weight to place on the advice by its source credibility (Harvey et al., 2000). Many web site design features incorporate credibility indicators to help users assess the advisors' authority, competence, and reliability (Fritch and Cromwell, 2001). Credible sources are influential when people have limited expertise relative to the decision task. This suggests characteristics of advice source credibility may influence advice taking.

Finally, people consider their ability to predict the advisor's motives and the risk of getting bad advice. Greater certainty in predicting motives and risks, knowing the expertise of the advisor, and an on-going relationship with the advisor leads to greater trust in the advisor, leading to greater influence of the advice (Yaniv, 2004). Thus, people weigh advice based on their own expertise, the advisor's expertise, and an assessment of advice quality.

Online Advice

The online context is an appropriate domain in which to test advice taking since there are varying degrees of expertise by those accessing 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 offline experience as Internet users cannot depend on all five senses to make decisions. They must rely on limited representations such as graphics and text descriptions. 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 (Schneiderman, 2000). Yet these guidelines differ in how well they influence user confidence. Online advice taking is important because of its unique setting comprising high risk, uncertainty and interdependence among potentially anonymous entities (Bhattacherjee, 2002).

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. These algorithms and models may perform well, but typically do not provide complete explanations of their advice. Thus investors either decide to trust and follow the recommendations or reject them. Research has shown novices are more willing to rely on computer aids and achieve greater decision performance (Mackay and Elam, 1992). Finally, the design of the computerized interface may impact how people rely on the advice (Silver, 1991). These findings suggest characteristics of the online advice source type may influence advice taking.

RESEARCH MODEL

In this study, decision making is modeled as being affected by three variables: one variable related to the characteristics of the user and two variables concerning the characteristics of the online advice source.

The research model is tested in the online investment arena. This environment is an appropriate context because characteristics of the user and the decision setting have been shown to matter (Looney and Chatterjee, 2002). Also online investing is a growing phenomena taking place on the Internet and exhibits a variety of source types and credibility levels. Users must rely on their own abilities to make effective decisions online. The model includes the concept of online investment self-efficacy (OISE), which is defined as an individual's perceived capability to utilize online investing tools to make effective decisions. Online advice source type (ONADTYPE) refers to whether the advice comes from a human advisor or computerized algorithm. Online advice credibility (ONADCRED) refers to whether the advice comes from a source that is trustworthy and has expertise.
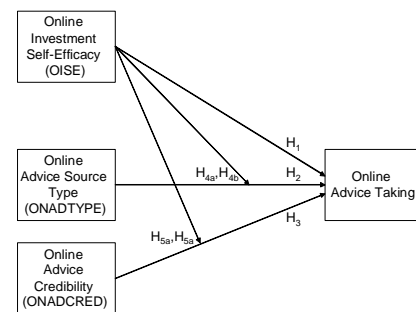

Figure 1. Research Model

Online Investment Self-Efficacy

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). Self-efficacy plays a critical role when using technology. In this study, OISE refers to an individual's perceived ability to utilize online tools to accomplish investing tasks.

One way users may attempt to resolve situational uncertainty is to rely on their own abilities, know-how, and opinions. 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 will be more likely to resolve uncertainty by relying on external advice. Those with higher levels of self-efficacy should be more certain about their ability to perform the task well on their own. These individuals will be more unlikely to resolve uncertainty through external means.

H1: Users with lower levels will weigh online advice more than those with higher levels of OISE.

Online Advice Source Type

People tend to trust other individuals because others have different life experiences and expertise and their perspective is based on sentient intellectual resources. 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). Thus, we expect users to take advice more often from a human advisor source than from a computerized algorithm source. The more people perceive similarities between themselves and the advisor, the greater the weight placed on the advice (Yaniv, 2004).

H2: Users with human advisors will weigh online advice more than those with computer algorithms.

Online Advice Credibility

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. 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. Conversely, weak (low) credibility indicators may encourage users to disregard the advice and to place greater weight on their own opinions.

H3: Users with high will weigh online advice more than those with low ONADCRED.

Interaction Effects

The first of two 2-way interactions is predicted for: OISE (high/low) X ONADTYPE (computer algorithm/human advisor). Users with lower OISE are most likely less confident and less comfortable making their decisions and as a result, less able to assess the attributes of advice sources. Yet, they need help with making their decisions. Being less confident and/or knowledgeable about the facets of the task, they may not understand or trust the computerized black box algorithms and models that typically do not provide adequate explanations of their analysis techniques. Thus, those with lower OISE should be more comfortable interacting with a human advisor than a computerized advice source. Those with lower OISE should more readily understand and trust advice coming from a human source.

H4a: Users with lower levels of OISE will weigh online advice from a human advisor more than from a computer algorithm.

Users with higher OISE are likely highly confident and very comfortable assessing the attributes of advice content on their own. Those with higher OISE should assess the quality of the advice for each source type similarly. Given the strong confidence and comfort in assessing the advice, users with higher OISE should be equally skeptical or accepting of advice from a human advisor or computer algorithm.

H4b: Users with higher levels of OISE will weigh online advice from a human advisor not differently than from a computer algorithm.

The second 2-way interaction is predicted for: OISE X ONADCRED. Users with lower OISE will react more to measures of source credibility more than those with higher OISE. Those with lower OISE should assess the quality of the advice by examining any information available to determine whether to rely on the advice.

H5a: Users with lower levels of OISE will weigh online advice with high ONADCRED more than advice with low ONADCRED.

Users with higher OISE are likely more certain in their abilities and very comfortable assessing the attributes of advice content. Those with higher OISE should assess the quality of the advice regardless of ONADCRED and may not use the source credibility information to determine how much weight to place on the advice. Given their strong certainty and comfort, users with higher OISE should be equally skeptical or accepting of advice from either a high or low credibility source.

H5b: Users with higher levels of OISE will weigh online advice with high ONADCRED not differently than advice with low ONADCRED.

METHODOLOGY

Subjects and Task

This study involved 429 undergraduates enrolled in business courses at three large universities. This sample was purposefully chosen. First, we required the manipulation of OISE so inexperienced online investors were sought. Self-efficacy beliefs of inexperienced individuals are more easily modifiable, facilitating a strong test of the theory. Second, online investors tend to be computer-savvy. Varying degrees of computing skills could plausibly contaminate results (Mackay and Elam, 1992).

The experimental task was designed to be a typical task that online investors perform, and thus one that subjects might perform as novice investors. Pilot tests indicated the subject pool had sufficient understanding of the task. Subjects received course credit for their participation and were eligible to earn a prize based on their decision quality to encourage performance. All experimental sessions were held in campus computer labs. First, subjects completed a pretest then 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 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.

All subjects saw identical stock information. Subjects were asked for their initial investment allocations. 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. Then they were allowed to update their investment allocations. Subjects then answered manipulation check and post-task questions.

Independent Variables

Three variables were manipulated in this study: OISE, ONADTYPE and ONADCRED. 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. ONADTYPE was manipulated by a picture and statement regarding whether the advice source was a computerized algorithm or a human advisor. ONADCRED was manipulated through statements about whether the advice source was highly trustworthy with high expertise (high) or not trustworthy with little expertise (low).

Dependent Variables

One dependent variable, online advice taking, was examined. Following Yaniv (2004), online advice taking was calculated by the difference between the stock allocation pre-advice and post-advice. This difference was divided by the total possible allocation change to calculate the amount of weight placed on the advice.

RESULTS

Manipulation Checks

Prior to testing the hypotheses, manipulation checks were analyzed to confirm the effectiveness of experimental treatments. ANOVAs were conducted using the treatment groups as independent variables and the manipulation check item scores as the dependent variables. No unexpected patterns across groups or interaction effects were significant. Subjects in different treatments perceived differences as anticipated.

Hypothesis Testing

As anticipated, self-doubting users (M=.368) were influenced by the online advice significantly more than those who deemed themselves as capable online investors (M=.261), $F(1,418)=8.123$, $p<0.01$. Hypothesis H1 was supported. Those receiving online advice from a human advisor (M=.324) did not weigh the advice more heavily than those receiving advice from a computer algorithm (M=.304), $F(1,418)<1$, ns. Hypothesis H2 was not supported. Those receiving advice from a more credible source (M=.539) were influence by the online advice significantly more than those receiving advice from a less

credible source (M=.089), $F(1,418)=144.047$, $p<0.001$. Hypothesis H3 was supported.

The OISE X ONADTYPE interaction term was not significant, $F(1,418)<1$, ns. Those with lower levels of OISE did not significantly differ in terms of online advice taking when confronted with a human (M=.366) and a computer (M=.369) online advice source. Similarly, those with higher levels of OISE did not significantly differ in terms of influence when dealing with a human (M=.282) and a computer (M=.239) ONADTYPE. Hypothesis H4a was not supported, whereas hypothesis H4b was supported.

The OISE X ONADCRED interaction term was significant, $F(1,418)=7.661$, $p<0.01$. Given the significant interaction term, to test H5a and H5b simple effects were examined. As expected, those with lower levels of OISE were influenced by advice from a highly credible source (M=.645) significantly more than a less credible source (M=.090), $F(1,209)=96.978$, $p<0.001$. Unexpectedly, those with higher levels of OISE weighed a highly credible source (M = .434) significantly more than a less credible source (M = .087), $F(1, 209) = 49.371$, $p < 0.001$. Hypothesis H5a was supported, whereas hypothesis H5b was not supported.

DISCUSSION

This study found that users with higher levels of task-specific self-efficacy are less likely to take advice. Online design features were also shown to influence advice taking. High source credibility led to greater advice taking. Contrary to expectations, source credibility appears to matter even when users have certainty in their own capabilities. This study illustrates the importance of disclosing credibility information to all users. Finally, advice source type had little influence on users.

Limitations

The findings from any study must be assessed in light of the study's limitations. The increased control afforded by a laboratory experiment must be traded off against the inherent limitations of the approach, primarily that of generalizability.

To adequately test the research model, we needed to manipulate OISE and find subjects that were computer-savvy. This goal led to the selection of student subjects. 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. Student subjects typically differ from experienced investors in two ways: less experience with the problem domain and less motivation to perform the task. Our subjects had experience using web-based applications to complete information tasks and had conceptual and hands-on experience from two practice sessions. They understood the context and the task. Subjects were offered course credit and prize incentives to increase their motivation to perform well.

The task involved allocating dollars to two pre-selected stocks which may limit the generalizability of these findings to tasks involving advice in similar settings. Also, individual subjects were given one piece of advice with little explanation behind it. In real-life situations, users would more likely have a mix of information.

Implications for Research

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, prospect theory suggests people experience loss aversion and they are more sensitive to decreases in their wealth than to increases.

People seek advice for a variety of reasons to: reduce their risk, reduce search time, learn how to use information, learn new information, determine social positioning, reduce discrepancies in information they have, get rewards or belong to a group (Yaniv 2004,). Future research is needed to study how other motivations for seeking advice influence online advice taking.

Another major contribution of our study implies there are consequences to task-specific self-efficacy beliefs that may be relatively malleable and evolve over time. In addition, the magnitude and strength of task-specific self-efficacy may vary depending on prevailing environmental conditions. We would not expect an individual to exhibit the similar levels of investment self-efficacy in fluctuating market conditions. Bull markets are likely to induce a more robust sense of OISE, whereas bear markets should temper it. Future research efforts are needed to understand the temporal and environmental mechanisms prompting advice taking behavior.

This study examines two specific variables concerning the characteristics of the online advice source (its type and credibility). Future studies could extend the model by examining measures such as the reasoning behind the advice given. Additionally, this study found people did not react as predicted to advice from a computer algorithm or a human advisor given ONADTYPE. Future research should study when advice source types matter.

Implications for Practice

Online brokerage firms, who are known to be lacking in terms of advice compared to full-service firms (Looney and Chaterjee, 2002), would be well-advised to craft marketing messages targeted at efficacious individuals. One online brokerage firm recently launched an advertising campaign embracing the slogan "You're in Control," which captures the essence of OISE. Brokerage firms should incorporate advice clearly into their systems or provide alternative means for getting advice including gaining access to a human advisor.

This research can also contribute to the broader investment community. 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 so users can make informed investment decisions.

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