To Risk or Not to Risk? Improving Financial Risk-Taking of Older Adults by Online Social Information

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ABSTRACT
Increasing number of older adults manage their retirement savings online. A crucial element of better management is to take rational financial risk – to strike a reasonable balance between expected gain and loss under uncertainty. With the emergence of Web 2.0 technologies, social trading networks can help individuals make better financial decisions by providing information about others' actions. It is, however, unclear whether these resources is beneficial to older adult's own financial decisions, especially because older adults are vulnerable to poor risk management. To address this question, we devise an experiment that improves upon an existing experimental economic task. We find that both peer information (detailed choices by a few individuals) and majority information (aggregated choices of the crowd) help older adults make more risk-neutral decisions. Furthermore, the combination of peer and majority information corrects more mistakes of more risk-averse older adults.

Author Keywords
Social information; decision-making; risk-taking; older adults; experience-based task.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Older adults represent an increasing proportion of the global population and hold a disproportionately large share of total personal wealth [39]. By 2020, adults aged 65 and over are expected to own one-third of all publicly held stocks in America [2]. To accommodate the growing "silver industry", the financial industry offers a variety of retirement investment plans and investment vehicles. Product variety and complexity inevitably require older adults to make better financial decisions. Although popular stereotypes suggest that older adults are more risk-averse than younger adults, economic and psychological studies show that older people generally make less optimal decisions than younger adults in financial situations and take risks in situations that require risk-averse behaviors (e.g., retirement saving management) [24, 30].

Older adults transition from information receivers to potential information contributors under emerging Web 2.0 technologies [4]. Social information (e.g. rating, comments, polls) can be more easily accessed by aging adults, and has great potential in helping older adults make better financial decisions by learning from others' experience.

Figure 1 Screenshot of ZuluTrade, a social trading website. Member's investment portfolios can be shared and followed.

Two types of social information are commonly found on the Web: (1) peer information – detailed choices by a few individuals, and (2) majority information – aggregated statistics about the choices of the crowd. For example, when people shop online, users can share their purchasing activities via social networking websites such as Twitter or Facebook, which provide other people with detailed

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individual choices. Some websites provide users with majority information, such as average ratings or total number of buyers of different products. In the finance domain, social trading networks, a type of online financial platforms, integrate social features to help users make decisions. For example, eToro and ZuluTrade let members share their investment decisions with explicit trading information and provide details beyond traditional financial forums that discuss only users' ideas (Figure 1). Geezeo and Wesabe allow users track their financial details. Two million households used these sites in 2008, and according to a Wall Street Journal report [19], that number is expected to jump to 16 million households within 10 years. As more older adults use the Internet to manage their financial assets [11], social information may also make aging adults feel vulnerable to risky investment options and fraudulent marketing practices [40]. Although important, there is still a general lack of research on how the online social systems influence financial decision-making behaviors. While it is usually difficult if not impossible to inform "correct" decisions (as they are either unknown in advance or hard to define), one reasonable and crucial objective for designers of online financial websites should be to help older adults manage risks better. As researchers of Computer Supported Cooperative Work (CSCW), we aim in this paper to understand whether the majority information and peer information, the social cues used in social trading networks can encourage rational risk-taking behavior among older adults.

Financial decision-making is a complex process that involves diverse variables, such as the domain knowledge or the personal financial condition of users. To clearly identify the sources of potential social influence, we conducted a lab-controlled study as the first step. Moreover, financial risk-taking is an experience-based decision-making process, in which the risk must be gauged empirically through the past experiences. Beyond the decision-making by users' own experiences, social trading networks encourage social learning by allowing the user to learn from the successes and failures of others, continually and gradually [27]. In recent years, several HCI and CSCW studies have investigated the influence of social cues on younger users' choice making [15, 22, 31, 32, 41], but the tasks used in these studies are description-based tasks, in which people make the decisions simply based on the descriptions of different options. This cannot represent the scenarios commonly encountered by older adults' risk management as they make continuous, long-term financial decisions such as retirement investment. Instead, our study builds on Knutson and Kuhnen's Behavioral Investment Allocation Strategy (BIAS) task and its subsequent modifications.

BIAS task is an experimental, experience-based task that investigates risk-taking behavior by minimizing the influence of participants' real-world financial knowledge [21, 29]. Furthermore, the BIAS task was designed to have a clear definition of rational risk-neutral choice, which helps us to investigate and highlight the irrational aspects of financial decisions.

Through the study, we are interested in understanding how social information commonly found on the social trading networks may influence risk-taking behavior. In particular, we are interested in whether providing older adults with peer information, majority information, and the combination of the two types of information, are effective in encouraging older adults to better manage risk.

SOCIAL TRADING NETWORKS

Financial trading was centered on the relationship between customers and brokers. Now with the surveillance of Web 2.0 technologies, it becomes possible to gather user-generated financial contents and provide users a new way of analyzing financial decisions by integrating other decision-makers' real-time trading data feed. Social trading networks have emerged in recent years, through the social networking websites. Users of social trading networks can easily look up other users' trading performance as well as the descriptive data of the crowd.

Figure 2. Screenshot of Stocktwits, where users can view the popularity and crowd sentiment towards an asset.

Social trading networks have several advantages over the traditional trading channels. Enabling transparent trading information flow, social trading networks make financial information of specific customer segments accessible to users according to users' own interest. For example, older adults can use the platform to understand the investment decisions of their peers with a similar financial situation and comparable risk management needs. Second, through information sharing, social trading offers investors the opportunity to work collaboratively with others on financial decisions. Moreover, financial systems could generate wisdom of the crowd [34], since cash incentive is the key driving force behind optimal rational crowd intelligence.

Although a variety of social trading networks platforms are rapidly emerging, there are mainly two categories: integrate social information of (1) other users of the platforms, and (2) users' existing social network. For example, eToro allows users to view other users' portfolios and to place a trade exactly like theirs. Other applications such as Stocktwits or Likefolio enable users to connect existing social networks, including Facebook and Twitter, to collect crowd opinions towards a specific asset (Figure 2).

RELATED WORK

Online financial decision-making in the social trading networks is collaborative and collective in nature. The HCI and CSCW communities have put increasing research efforts into understanding and measuring online social dynamic systems that investigate how users consume social networks content [25], share knowledge among social networks [14], and make choices based on social cues [31, 32]. Brief summaries of two relevant research areas follow.

Preferential Choice

People use the information on the web to help them make daily decisions, such as choosing movies, picking out clothes, or buying stock. To make these decisions, people collect information about options and engage in a process of comparison that ends with a choice. Understanding and facilitating consumers' choice-making process has received increased attention from the CSCW and HCI communities [22]. Jameson defined the term "preferential choice" to distinguish from "non-preferential choice" that exist only in terms of the correct solutions – for example, "which button needs to be clicked to send the email" [17]. For instance, in online shopping platforms or cultural markets (e.g. movie-booking systems), the social information gathered is subject to personal interest and preference. To investigate the preferential choice-making process, researchers commonly use the description-based decision-making tasks that provide complete information about probabilities and outcomes of each choice. Some studies used this type of experimental task to examine the influence of different kinds of information on people's online decision-making behaviors [31, 32]. By adding different interface cues (e.g. credibility of the information source, narrative of the information, and social cues), these studies identify people's preferential choices towards the descriptions of options with respect to the cues.

However, preferential choice making is not common in financial settings. Of particular concern to financial decisions is the phenomenon that people usually make decisions from experience, based on trends of recent payoffs from the investments of specific financial assets, because it is usually easier to judge the quality of a decision based on direct, perceived consequences. Although participants have their preferential choices based on their preferred risk-taking strategy, there often exists an optimal choice based on economic theories. Thus, decisions resulting from experience-based tasks, such as the Iowa Gambling Task and BIAS (refer to [24] for a complete review), have been extensively studied for these situations. In these tasks, explicit information about probabilities and outcomes is not shown and participants must rely on task experience acquired through task feedback. Thus, to better understand how online social information can influence older adults' financial decision-making behaviors, our current study adopts the BIAS task, which allows us to directly measure whether subjects are making better risk management in an experience-based task setting.

Social Influence

In a nutshell, social influence takes place when people adjust their beliefs and behaviors with respect to others whom they feel similar, in accordance with psychological principles or the majority of an individual's referent social group [8]. A number of empirical studies have considered effects of social influence in various settings, including education, beliefs, preferences, and financial decision making within physical groups [5, 20]. Recent research extends this investigation with the deployment of social media [12]. Kim explored common social cues used in the health domain and found that these cues had a strong influence on decision preference among young people, further revealing more influence between cues in which bandwagon effects were shown [31]. A similar finding was reported in [41]. By using tasks deployed on Mechanical Turk, Zeinab et al. found the information from the crowd had a greater effect than a friend's recommendation on the willingness of an individual to choose an option. This implies that majority information may have a stronger influence than peer information on people's online decisions. While generating social information or enabling social interaction among users provides a valuable reference source for people, biased social information can have a negative impact in settings that have optimal choice. In a social visualization study, Hullman et al. [15] found that unbiased social signals lead to fewer visual perception errors than those resulting from non-social settings and biased signals, which have converse effects.

Although the above studies show the importance of social influence on people's judgments, they have not addressed the current focus on financial risk-taking behaviors. Unlike the social influence in preferential choice making, the social influence in financial decision-making is actually a social learning process, as people need to make continuous decisions by combining own judgments with ideas from others. Social learning was found effective in improving the quality of online collaborative knowledge sharing [36] and crowdsourcing tasks [23]. In the finance domain, Wei Pan etc. has conducted the first study with social trading networks [37]. By analyzing the dataset from eToro, they found that social influence plays a significant role in users' trades, especially when the trading information consists of higher uncertainty. Furthermore, in his newly published book *Social Physics* [27], Alex Pentland summarizes Wei Pan's findings as the effects of social learning and idea flow through the social network, where the traders who have the right balance and diversity of peer ideas gain more than individual traders. However, the monetary gain doesn't necessary be equal to rational decisions or better risk management. In a certain period, active risk-seeking investors (or gamblers) may have better profits than rational investors, but this trading strategy may not be suitable for older adults in managing their retirement investment. Also, in [37], they did not tease apart majority information and peer information. Furthermore, the real-world data from eToro may not be ideal for understanding the rational aspects of the influence of social information, since the investment choices could be influenced by other confounding variables such as the user's financial domain knowledge and motivation of investment. As online interface designers, we would like to further understand the influence of specific types of social information on older adults' decisions.

OLDER ADULTS' RISK-TAKING AND DECISION BIASES

Risk is usually associated with uncertainty in outcomes when people make decisions [28]. If the provided information is complex and uncertain, individuals tend to use heuristics to make decisions [35]. For example, in the context of financial decision-making, people may estimate good investment vehicle merely relying on its short-term performance. As Gilbert pointed out, when there is little detailed information about the future, people tend to use their affect in the moment as a proxy for what the future will be [13]. This strategy simplifies cognitive workload, but results in sub-optimal decisions, that is, decisions that do not maximize monetary payoffs on average. While such affective forecasting errors may influence decisions for everyone, the limits of older adults' recollections of the past and lack of up-to-date domain knowledge make this forecasting error especially impactful [38]. In addition, from the developmental perspective, Socioemotional Selectivity Theory [6] suggests that older adults tend to optimize emotional experience when growing old, which involves reducing negative arousal during anticipation of negative events. Although these affective regulations may be healthy for balancing emotional experience and optimizing well-being, they may have negative effects on financial planning such as blunted loss anticipation.

In the decision-from-experience scenarios, the influence of decision bias has a significant effect on older adults. In a meta-review of aging risk-taking research, Mata [24] concluded that aging adults made more sub-optimal choices than younger individuals in an experience-based task, while no such difference was observed in a description-based task because learning deficits have stronger effects on decision-making from experience.

However, we postulate that the social information aggregated in the social trading platforms could modulate the decision bias for two reasons. First, the transparent information sharing can serve as the reinforcement and correction of older adults' own memory thereby decreasing the uncertainty of information and the influence of older adults' recollections limits. Second, the continuous and gradual information from peers and crowd creates an ideal environment to encourage social learning. In such situation, older adults can improve their investment strategies through the interaction between social learning with individual learning. By allowing the ideas flow, the social information provided may benefit older adults to make more risk-neutral decisions by modulating the influence of the learning deficits as well as the influence of affective regulation on proneness for financial decision mistakes.

Hence, the current study proposes the following hypotheses:

H1: Majority information can improve older adults' financial risk management.

H2: Peer information can improve older adults' financial risk management.

As reported in [31] and [41], the majority information has a stronger influence than peer information when users make decisions. We expect similar result in the experience-based decision-making settings, as the bandwagon effect is associated with this type of information:

H3: Majority information has a larger effect than peer information.

Aging adults have a more salient age identity and influence among their peer age group than younger adults [9], as previous studies have shown that social effects play an important role in seniors' purchasing behaviors and retirement savings decisions [10]. This finding strongly indicates that social influence could affect risk-taking behaviors.

H4: Peer information and majority information CAN modulate older adults' risk-taking attitude.

By a large-scale survey on older adults' technology use, the Internet usage among aged 65+ has increased to 40%, but only around 5% of those aged 85+ were Internet users [7]. Therefore, we choose the population group aged 65 on average as the "older adults" investigated in our study.

METHODOLOGY

We conducted a laboratory experiment modified from the BIAS task to incorporate social information. The risk-taking behaviors defined in the BIAS task are consistent with the anticipatory neural activity using event-related fMRI [21]. Moreover, although the BIAS task is an abstract version of real-world financial decision-making, it was demonstrated to have ecological validity: subjects who made more risk-neutral choices in the experiment also possessed more assets in the real world settings [29].

BIAS Task

In the BIAS task, subjects were required to allocate their money among three options: two stocks that yield variable returns, and one bond that yields a constant return of $1 per trial. One stock is "good" and generates a higher expected payoff (+$10 with 50% probability, $0 with 25% probability, -$10 with 25% probability), and the other is "bad" and generates a lower expected payoff (-$10 with 50% probability, $0 with 25% probability, +$10 with 25% probability). For each trial, earnings were drawn independently from these distributions. In each block of trials, the computer randomly selected one to be the "good" stock and the other one to be "bad" stock, but the subject remained unaware and can only infer which one was good from previous gains and losses of the stocks' performances.

During each trial, subjects first saw the three options (Anticipation) and then selected one of three assets on the next page (Choose). After the selection, their earnings for that trial, total earnings, and the outcomes of all assets were displayed and followed by the page of a fixations cross (Fixation) (Figure 3). The participants were asked to perform the task at their own pace and were not allowed to take notes.

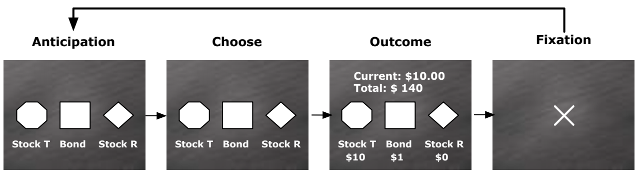


Figure 3. The conceptual workflow of each trial of BIAS task

Given that the actual monetary amounts at stake in each trial were small (−$1 to $1, since one-tenth of the task earning was given as the final reimbursement), the task defined the rational choice as the choice a risk-neutral, perfect Bayesian updater would make to maximize expected monetary return [27].

This risk-neutral actor updates the possibility of each option that generates the highest expected payoff based on Bayes' rule. To be specific, he or she would pick a stock i if the dividend D_k^i of this stock is at least as large as the bond earnings ($1) during trial k, that is, if: $E\left[D_k^i \middle| I_{K-1}\right] \geq 1,$ where the I_{K-1} is the set of information up to trial k-1. Outcomes of stocks in each block were randomly generated from the probability distributions. From multiple sets of five blocks of outcomes, we selected the sets that the risk-neutral model earned $75 in each to control the difficulty across conditions.

For each trial, any choice that departs from the rational choice belongs to one of the three types of mistakes. When the rational choice is a riskless option (i.e., a bond) but the subject chooses a risky option (i.e., a stock), it is categorized as a **risk-seeking mistake (RSM)**. When the rational choice is a risky option (i.e., a stock) with the optimal expected payoff, but the subject chooses a riskless option (i.e., a bond), it is categorized as a **risk-averse mistake (RAM)**. If the subject chooses the other stock, then it is categorized as a **confusion mistake (CM)**, which the study does not analyze.

Social Information Modeling

Majority information

In his book *The Wisdom of Crowds,* Surowiecki suggests that aggregating the imperfect, distributed knowledge of a large group of people would yield better intelligence [34]. Alternatively, as proposed in theory of information cascade, if a group of people in a population exerts a stronger influence on others, the "herding" effect may cause others in the same population to abandon their own information in favor of following others [3]. Similarly, in the social media community, Sundar defines the behavior of blindly relying on the collective opinion of others as the "bandwagon effect" [33]. However, in a recent journal paper [1], Acemoglu demonstrates through social network analysis that "as networks of people grow larger, they'll usually tend to converge on an accurate understanding of information distributed among them, even if individual members of the network can observe only their nearby neighbors."

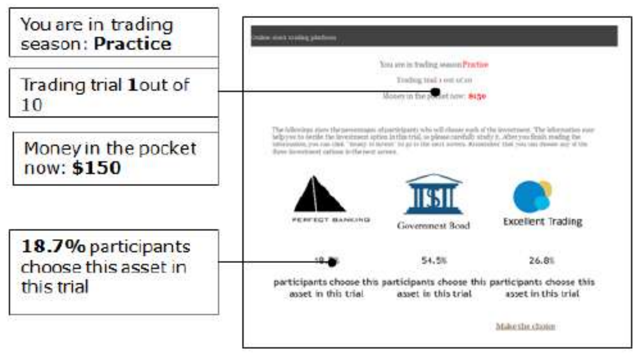


Figure 4. Majority information interface

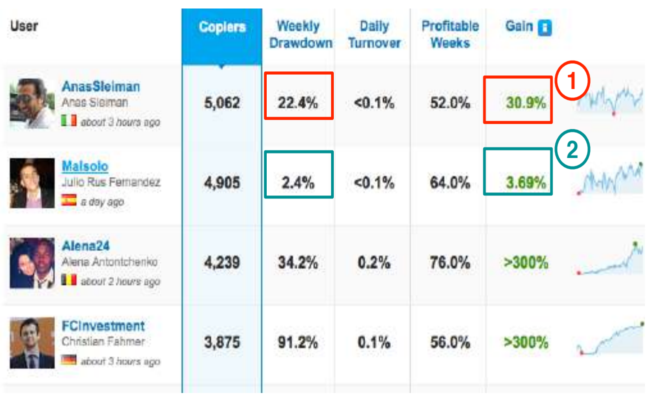
To what extent of the majority information consists of the rational decision is a sophisticated economic question that involves many contextual factors and ongoing debates of the representative modeling of the real world, and is beyond the scope of this current paper. In our study, we modeled the majority information based on classic economics theory to maximize expected utilities [16]. We assumed that most of the decision-makers would behave rationally in our experiment. Thus, we generated the proportion based on the expected payoff. For example, the option with the highest expected payoff has the largest reported proportion, which is also the choice of a perfectly rational agent. The majority information assumption was proved by our experimental result. In the 1-5 blocks (the blocks without social information), participants made the average number of 4.51 rational choices in each block, which meant that around forty-five percent of people made the rational choice in each trial that consisted of the largest proportion among the three choices.

Figure 5. Example of payoff distribution within one block

Notably, in the experiment, the benefit of simply following the majority information was not obvious. Since the risk neutral agent chose the options with the highest *expected* payoff, not the options with *actual* payoff, the payoff of a risk-neutral choice at a certain period may be less than the risk-seeking or risk-averse strategy. We selected the distribution of stocks' outcomes that the risk-neutral actor earned \$75 in each of five blocks, which was an average of \$15 in each ten trials. Figure 5 shows an example of payoff distribution of a risk neutral agent's choice in a block of ten trials.

Peer information

Although according to classic economics theory we assumed that most of the people are risk-neutral in a transparent information environment, the individuals' decisions could be varied based on people's preferred risk-taking attitudes [25]. For example, in the webpage of most followed users in eToro (Figure 6), user 1 is a risk-seeking investor while user 2 is a risk-averse investor. Thus, in the attempt to simulate real world scenarios, we modeled peer information as the different attitudes of people risk-taking behaviors, from absolute risk-averse (the people who don't invest at all), risk-averse, risk neutral to risk-seeking.



User	Copiers	Weekly Drawdown	Daily Turnover	Profitable Weeks	Gain
AnasSleiman Anas Sleiman about 3 hours ago	5,062	22.4%	<0.1%	52.0%	30.9%
Malsolo Julio Rus Fernandez a day ago	4,905	2.4%	<0.1%	64.0%	3.69%
Alena24 Alena Antontchenko about 2 hours ago	4,239	34.2%	0.2%	76.0%	>300%
FCInvestment Christian Fahmer about 3 hours ago	3,875	91.2%	0.1%	56.0%	>300%

Figure 6. Screenshot of eToro Openbook's most followed users

The four virtual peers' choices are the choices made by four "ideal" agents with different utility functions that exhibit different levels of risk aversion, ideally to simulate the risk-taking attitudes present in a real-world population. Peer 1 is a risk-neutral, linear utility maximizer who always makes rational choices according to definition. Peers 2 and 3 make the choices as if they are risk-averse agents with the constant absolute risk averse (CARA) utility function: $1 - \exp(-a\ (10 + x))$ with a=0.5 for Peer 2 and a=0.0002 for Peer 3. Peer 4 is risk seeking with the agent's choices generated by the risk-seeking utility function $(150 + x)^2$. . The CARA utility function [25] can be only risk-averse with a concave function, while the risk-seeking function must be convex. We chose the parameters of the two functions different enough to make the distribution of virtual agents' choices distinguishable. The interfaces of majority information and peer information (Figure 4 and 7) are designed to be similar to the relevant webpages shown in the social trading networks platforms, that is, majority information with the crowd choice's indicator (Figure 2) and peer information with the performance of the selected individuals in the form of investment preference, current investment outcome, and line graph of the payoff trend (Figure 6).

Figure 7. Peer information interface, the upper part of this interface same as figure 4, except the majority information

Experimental Manipulations

In order to involve the social signal in the experiment, we told the participants in the social conditions that our system had already collected other participants' data and would extract the relevant information to help them play the task. Also, we specifically designed the task interface. In the login page of the experiment task, we randomized a number between 200 and 250 to inform participants of their user status: "Welcome to our online stock trading task. You are the XXX participant!" This number was required for participants to take notes to get the final reimbursement at the end of the experiment.

To avoid information sharing, participants were assigned to sit far apart and were not allowed to communicate.

Experiment Design

The study followed a between-subjects design with four conditions: 1) baseline condition; 2) with peer information; 3) with majority information; 4) with both peer information and majority information. Forty-eight participants (M= 62.08, SD = 5.59) were recruited from an aging volunteer organization in Singapore. All participants had basic computer skills and Internet experience (they had taken part in local senior computer classes). Before the study, we tested participants' knowledge of possibility. Only participants who understood the relevant concept were enrolled in our experiment.

The information a subject faced was different across the four conditions. In Condition 1 (baseline condition), each person observed only the realization of each stock and bond after each of the choices. In addition to information available in Condition 1, Group 2 participants had access to peer information and Group 3 participants had access to the majority information. In Group 4, all types of information available to Groups 2 and 3 were simultaneously shown to the participants, and the realization of the stock was shown after each choice was made.

Procedure

The participants were asked to read the instructions of the experiment upon arriving the experiment room. In the instructions, we showed participants the possibility of stocks' performance and reminded them, "Please use your best judgment to make the decision and the final reimbursement for your participation will be ten percent of your task earning." Before the start of the formal study, they had three blocks to practice the baseline task organized by the experimenters, during which the experimenters would answer any questions related to the interface and task rule to minimize adapting effects. After the formal study, the experimenters debriefed the participants and conducted an interview with them. The whole experiment took approximately two hours.

Each participant began with $150 virtual money. At the end of the experiment, one-tenth of the virtual money left was given as a reimbursement. The whole experiment consisted of 10 blocks, with 10 trials in each block. All participants performed baseline task in the first stage, comprised of five blocks, and then were randomly assigned to four groups for the second stage, which was comprised of another five blocks.

DATA ANALYSIS

Social Information on Risk-neutral Choice-Making

At first, to understand the effects of social information on older adults' risk-neutral financial decisions, we conducted a three-way ANOVA on the number of risk-neutral choice as dependent variable, with stages (blocks 1-5 vs. blocks 6-10), majority (with or without), and peer (with or without) information as independent variables. The two-way interaction between stage and majority information is significant *($F(1,44)=5.23$, $p<0.05$, $\eta^2=0.11$)*.

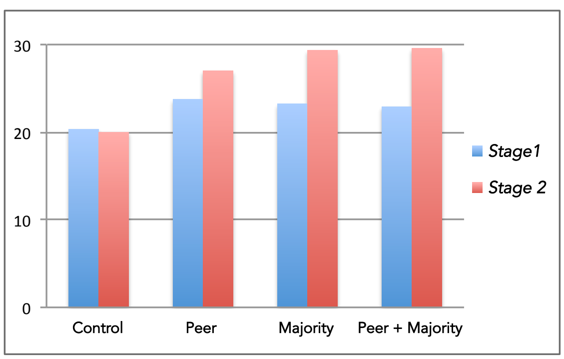


Figure 8. Average number of risk-neutral choices

To understand this two-way interaction, we first performed an ANOVA with the number of the risk-neutral choice as dependent variable in the baseline condition (first 5 blocks), which yielded a non-significant risk-neutral choice * group interaction, *($F(3,44)=0.72$ $p=0.545$, $\eta^2=0.05$)*, indicating that there was no individual difference on the ability to perform task among the participants of four groups. We then performed a repeated ANOVA on risk-neutral choice with stages as independent variable, and found that, except for group 1, which showed a non-significant result, the difference between stages (first and last 5 blocks) was significant in all three groups *(($F(1, 11)=5.616$, $p<0.05$, $\eta^2=0.34$)* in group 4 (with peer information and majority information), *($F(1, 11)=5.965$, $p<0.05$, $\eta^2=0.35$)* in group 3 (with majority information), and *($F(1, 11)=4.804$, $p=0.05$, $\eta^2=0.30$)* in group 2 (with peer information)*)*. The results suggested that after controlling individual differences, participants had made more risk-neutral choices. These indicated that both peer information and majority information helped them to correct some amounts of heuristic forecasting bias in the decision-making process. Therefore, H1 and H2 were supported (Figure 8).

To further explore the differences between effects of majority information and peer information, we conducted a two-way ANOVA on risk-neutral choice in only stage 2 (the last 5 blocks). The results showed that there was no significant interaction between the effects of w/without peer and w/without majority on number of risk-neutral choice, *($F(1, 44)=2.48$, $p=0.123$, $\eta^2=0.05$)* and no significant difference in risk-neutral choice between w/without peer *($p=0.098$, $\eta^2=0.06$)* but there was a significant difference between w/without *majority ($p<0.01$, $\eta^2=0.15$, $d=0.748$)*. The Cohen's d indicated that the result had a large effect size. Simple effects analysis showed that there were significantly more risk-neutral choices with the majority information than without the majority information (*$p<.05$*). This result was consistent with the previous studies on social cues [31, 41], which indicated that majority information had a larger effect on people's decisions than information from individuals. Thus, H3 was supported by the main effect.

Effect of Social Information on Risk Attitude

We defined "corrections" of each type of mistake (RSM and RAM) as the difference between the number of mistakes in the experimental condition (stage 2) and number of mistakes in the baseline condition (stage 1). We then calculated the correlation between the number of RAMs the participants made in the baseline condition (which reflected their risk attitude, i.e., how risk-averse they were) with the number of corrections of each type of mistake in order to study to what extent the effects of social information depended on participants' risk attitude. We found that the correlation was significant in only group 4 (with both peer and majority information provided), in which we found that participants who were more risk-averse tended to have more corrections of risk-averse mistakes *($r=-0.622$, $p<0.05$) and* fewer corrections of risk-seeking mistakes *($r=0.869$, $p<0.001$)*. In other words, the social information helped to correct the most mistakes of the same risk-taking type. Specifically, risk-averse participants corrected more RAMs than RSMs, while risk-seeking participants corrected more RSMs than RAMs. In summary, H4 was partly supported by the findings that social information could be effective in nudging participants towards making more risk-neutral decisions and adjusting their own biased risk-taking attitudes.

Strategies used in performing the task

After the formal experiment, the researchers debriefed the participants and then conducted a short interview regarding the investment strategies applied to the task and in real life.

Attitudes towards the BIAS task

Although the BIAS task is a shorter and simpler version than the financial decision-making in real world scenarios, participants still expressed that it was relatively difficult to make decisions: "*The task is a little complex to me. I forget the deep mathematics already, but I can still make decisions by memorizing the good stock.*" When this participant was asked about the way to define "good stock," his answer was a simpler decision-making strategy confounded with using heuristics: *"The one shows $10 dollar more often.*" The participants made risk-taking mistakes with respect to their particular risk-taking attitudes: "*When I gather enough money, I will continually buy bonds,*" or "*I will always choose the good stock, because in the long run it will make profits*."

Attitudes towards social information

Before the experiment debriefing, the participants in the social information condition (groups 2, 3, 4) did not express concerns about the authenticity of the social information. They also shared their strategies with us, which were similar to the real world social effects. In the majority information condition: "*When I get confused by the stock price, I will listen to the others' opinion*," "*I don't have enough financial knowledge, thus I just follow the majority choice, which is a safer way not to lose the game,*" or "*I think I am better with financial decisions, so I make decisions on my own. However, I will refer to others' choices when I forget something*." In the peer information condition, the situation was more complex, as the participants had to identify "which peer made better financial decisions": "*I keep an eye on their performance, and try to pick the best one to follow*"; "*Like real life, I consult my friend's opinion, but I do not totally believe their decisions. So I choose to compare the opinion leader's choice with my choice, then make the final decision*."

Strategies in real life

There were a surprisingly high proportion of participants investing in the stock market. In their experience, the social factors played an important role: "*My sister invests in the stock market, so I just follow her*," "*I pay attention to the company fame and its recent stock payoff. I do not believe in experts' opinions, because they make profits from my decisions and may cheat me. However, I believe my friends' opinions,*" and "*Currently, most of our older people put our savings in the bank. It's much safer and I don't have enough money to make risky choices.*" Our participants showed strong interest in asset management but relied on limited information sources (friends, intuition about majority).

DISCUSSION AND IMPLICATION

The findings in this work support that social information improves older adults' financial risk-taking. Through the social learning, older adults can modulate the negative influence of decision bias caused by heuristic forecasting and learning deficits. As a starting point, our study investigates the social information used in social trading networks. The next step of our research should consider the effects of tie strengths of older adults' existing social networks. Although there is little existing implementations of utilizing users' social ties in current social trading platforms, the potential implications may be promising. A recent study on social ties in teams' collaborative problem solving suggests that the strongest ties have an effect on the final performance [26]. We would like to know whether the strongest social tie of older adults has a larger effect than majority information. However, as noted by Alex Pentland [27], if the social networks of user's circle are too tight while with the similar characteristics, it will limit the payoff of social learning. Thus, the implications of tuning down effects of social tie should be investigated.

Our study examines the rational aspect of financial risk-taking. It is not equivalent to the "correct" decision with respect to the particular individual's situation. The "correct" decision for an individual is hard to define without knowing his or her contextual information. For example, the purchase of an asset may be a rational decision in the absolute sense, but it could impede the older adult's ability to pay for a hospital visit, which is more important to the older adult's well-being. Thus, requiring older users to report additional information such as health conditions, personal assets, and daily expenses, the social trading platforms can selectively present the social information gathered from people with similar backgrounds, in order to help older adults to make more potentially "correct" decisions. Our current study focuses on the financial context. We expect that the same results also apply to other situations where decisions are made under uncertainty and by prior experience, such as choosing an online education service, online labor market (e.g., Elance.com, Guru.com), or online storefronts (e.g., Zaarly.com). Future studies should investigate whether the same effects can be found in these settings.

Our results have important implications for designers of online financial platforms. Presenting social information from others or crowd can sway older users' decisions and modulate their risk-taking attitudes, thereby influencing factors up to the quality of risk management, such as participation and long-term adoption. The results also imply that designs of financial websites should more clearly visualize both descriptive information of risk and experience-based information of risk in forms that help older adults improve the effectiveness of social learning thereby nudging them toward more risk-neutral behavior. Future research is needed to further test what/how both types of information should be presented to convey risk information, especially in a way that is effective for older investors. Given that experience-based learning is more effective for presenting rational risk-taking behavior, it may be beneficial to allow older adults to perform virtual investments and share this information with others, thus promoting the understanding of the risk involved. It is possible, for example, to allow older adults to engage in some form of a social game in which they share and compete with each other using virtual money. This approach would allow older adults to experience and learn the outcomes of different types of investment options, before they perform real world investment.

The contributions we make to online financial platforms design are based on a lab experiment that focuses on a limited environment and limited options. Clearly, actual financial decisions are more complex and involve more options. However, the *categories* of options of the real world asset allocation are often similar to the ones we used in the study –i.e., safe but less rewarding versus risky but more rewarding. Additionally, the same categories of investment assets are also commonly used to educate investors on how they should allocate their assets.

LIMITATIONS

There are several concerns worth discussing. First, the majority information was constructed based on the classical economics viewpoint that most people are rational in the open information environment. We acknowledge that it is possible that the majority decisions of users could be irrational in some specific scenarios. For example, a "bad information cascade" happened in a restricted information exchange environment (e.g. unbalanced information sharing between senior investors and common users). The current experiment therefore did not allow us to tease apart effects of social influence and rational decisions. In the next experiment, we plan to create conditions in which the majority information would lead participants further away from rational choices. We will then be able to test to what extent people "blindly" follow others, choose rationally instead of following others, or pursue a decision that is mixed between the two effects.

In addition, although we obtained significant results from the experiment indicating that social information had a strong effect on older adults' financial risk-taking behaviors, the sample size was still too small for us to induce more detailed explanations. Future research should conduct this study on a larger scale. This will allow us to analyze the actual dynamics of social influence on choice behavior. For example, an individual is possibly using a weighted average of his/her own and others' information to make investment decisions, and the weights may be heterogeneous across participants. Future research could also conduct analysis based on existing online corpus in situations with or without social information.

Lastly, since we conducted the experiment in Singapore, it was possible that cultural issues impacted the extent to how social information was interpreted and how risk was perceived. Future studies should consider replicating the studies in other countries.

CONCLUSION

In this paper, we have provided evidence suggesting that social information has an effect on older adults' financial decision-making behavior. Expanding an experience-based decision task, we found the unbiased aggregated social signal or individuals' choices could nudge older adults towards making better risk management in online financial decisions. The bandwagon effect was stronger than the peer effect. In addition, we found that the more risk-averse an older adult, the more influential the aggregates of social information. While social information is widely utilized in Web 2.0 platforms, to the best of our knowledge, our research is the first to embrace an experience-based task to investigate its influence on people's risk-taking behaviors. We argue that future online financial systems should consider incorporating this type of information as a design factor in improving people's financial well-being.

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