The Utilization of Robo-Advisors by Individual Investors: An Analysis Using Diffusion of Innovation and Information Search Frameworks

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This study examines the roles of internal and external search characteristics and attitudinal factors in investors' decisions to utilize robo-advisor-based platforms. Using the 2015 state-by-state National Financial Capability Study and Investor Survey, this study finds that the need to free up time, higher risk tolerance, higher subjective financial knowledge, and higher amounts of investable assets were positively associated with individual investors' adoption of robo-advisors. Additionally, the results from the interaction model indicates that individuals under 65 with a higher risk tolerance and greater perceived investment knowledge were more likely to use robo-advisors. Implications of the key findings for scholars, practitioners, and industry leaders are included.

Keywords: financial literacy, fintech, financial planning, information search, investment knowledge, robo-advisor

Intense debates continue about the comparisons between robo-advisors and traditional human financial advisors. Robo-advisory services (also referred to as robos) have become increasingly popular and have continued to increase in number since 2008. The economic recovery from the recent financial crisis has paved the way for financial technology (*fintech*) and financial digitalization to make financial services and products more cost-efficient and accessible for the majority of investors. The competition resulting from the emergence of robo-advisors has catalyzed a lower-fee environment and forced many traditional financial services firms to consider revising their fee structures or integrating robo-advisory platforms into their offerings to remain competitive in the market.

Meanwhile, traditional human financial advisors face challenges brought about by the increasing presence of robo-advisor-based services. Successful traditional client-facing financial advisors develop deep relationships with clients over time, invest more time in providing services, and also utilize quality administrative and executive support to manage and operate their advisory firms (Kitces, 2018). However, it is notable that some robo-advisor features, including easy accessibility, automated operations and portfolio management, portfolio recommendations, low human involvement, and the digitalized financial technology, may be attractive to different groups of users and contribute to the diversity of the financial planning and wealth management industry in terms of service delivery and investment digitalization.

In general, robo-advisors are computer-automated investment platforms. A typical user completes a questionnaire regarding the investment time horizon, goals, and risk tolerance. The robo-advisor then incorporates these answers into a complex programmed algorithm to generate an optimal customized portfolio for the client. Currently, U.S.-based robo-advisors, such as Betterment, Wealthfront, Schwab Intelligent Portfolio, and others are being utilized by early adopters, due to their lower cost compared to traditional human-involved financial advice systems (Rosenberg, 2018).

One key reason for the fast-growing robo-advisor platforms is the comparatively lower costs associated with their

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services. Using a dataset with 250 global robo-advisors, researchers showed that the average annual fee for traditional financial advisors was 0.7% of assets under management; whereas by comparison, fewer than 20% of the robo-advisory companies charged fees higher than 0.7%, and none of the robo-advisors that charged the higher fees were located in the United States. Additionally, robo-advisor utilization has been associated with increased investment confidence among the participating investors (Phoon & Koh, 2017). Some features and functionalities offered by robo-advisors, such as automatic deposits, rebalancing, tax-loss harvesting, and asset allocation of the portfolio, and so forth. simplify investment and portfolio management for users. In fact, according to a recent LendEDU report, almost half of millennials are intimidated when it comes to engaging with a human financial advisor (Brown, 2017). Therefore, robo-advisors are expected to play an even larger role in the future by effectively attracting potential new investors and, in the process, increasing the general financial advisory service inclusion, especially for segments of the population in their prime stage of wealth accumulation.

However, limited research to date has investigated robo-advisor adoption behavior. This study therefore addresses the need for a systematic framework to understand robo-advisor adoption and utilization among individuals and households. The diffusion of innovation theory (Rogers, 1962) and the information search model (Beales, Mazis, Salop, & Staelin, 1981) provide theoretical support for the analysis of the new developments in financial technology-based platforms and help understand the importance of information sources as they relate to the robo-advisor utilization decision-making process.

Literature Review and Hypotheses

Previous Research

There have been various definitions of the term "robo-advisor." For example, Sironi (2016) clearly defined robo-advisors as "automated investment solutions which engage individuals with digital tools featuring advanced customer experience," and robo-advisors are "conveniently supported by portfolio rebalancing techniques using trading algorithms" (p. 8). Fein (2015) depicted robo-advisors as "a growing number of Internet-based investment advisory services aimed at retail investors" (p. 2). Investors typically need to consider several factors when using financial advisors, including (a) minimum initial investment amount, (b) annual management fees, (c) investment products and asset allocation in the portfolio, (d) tax services, (e) goal-based planning, and (f) automation (Ludwig, 2018; Phoon & Koh, 2017). Several U.S.-based robo-advisors have also begun providing tax planning services to their clients along with sophisticated tax planning strategies such as "tax loss harvesting" (Phoon & Koh, 2017). Tax-planning features and goals-based investment advisory styles have also contributed to robo-advisors' popularity.

Successful robo-advisor platforms provide automated portfolio allocation techniques at a cost lower than the more conventional human interaction-based investment advisory services (Phoon & Koh, 2017). There are other benefits of robo-advisory platforms as well. For example, Salo (2017) summarized that robo-advisors usually offer more consistent and neutral investment recommendations than those offered by human advisors, as human nature may cause bias and inconsistency. Ease of use is another advantage that robos provide over human advisors. First, most robos require minimum information input and less frequent information update from clients. This format may be more convenient for those who wish to save their time. Additionally, robos provide easy accessibility to users, meaning that users can monitor and manage their portfolios via their computers or mobile devices without any time or other limitations.

There are, however, some factors preventing people from adopting robo-advisors. For example, according to a research poll conducted by LendEDU, although it is believed that millennials are the targeted users of robo-advisors, the majority (more than 75.7%) reported not having worked with any type of robo-advisor. The biggest reason behind this was that most millennials had never heard of robos, followed by their fear that robo-advisors may not be as efficient as human advisors in preventing potential losses (Brown, 2017). In the same report, those who showed a favorable attitude toward robos believed that the most important advantage stems from the easiness of initiating the investment process with robo-advisory platforms, followed by their constant accessibility, cost-efficiency, technology, and tax-efficiency. Moreover, LendEDU documented in another report that there might be some over-optimism among millennial robo-advisor users (Hamory, 2018). Interestingly, almost half (42.25%) of participating millennial investors expected robo-advisors to outperform the market. Since most robos recommend portfolios consisting of Exchange-traded funds ETFs and use passive management, it is more likely that the portfolio would track or sometimes even underperform the market. It is also surprising to see that most participants reported their investment horizon using robo-advisors as falling between 1 and 3 years, followed by 3–5 years; whereas, only 12.53% had long-term (10+years) investment goals.

As a segment of the fintech trend, robos have broadened the means of delivering financial advice. Traditionally, human financial advisory services could provide clients with customized benefits, including but not limited to accumulating wealth, generating investment returns, guiding financial behaviors, increasing financial well-being, and reaching long-term financial goals (Hanna & Lindamood, 2010; Joo & Grable 2001; Kim, Garman, & Sorhaindo, 2003; Marsden, Zick, & Mayer, 2011). However, concerns have been raised by researchers regarding trust issues and fiduciary versus suitability issues (Finke, Huston, & Waller, 2009; Redhead, 2011). More importantly, discussions have taken place about the costs and fees associated with seeking professional financial advice. Financial constraints may prevent some individuals and households from seeking financial help from experts, although the literature suggested that obtaining financial (counseling) advice is positively associated with desirable financial behaviors (Fan, 2017; Moreland, 2018). Specifically, most mid- to low-income households with lower financial literacy and capability are in fact the population that most needs professional financial help; however, those households usually have fewer financial resources to afford professional advice (e.g., Collins, 2012; Son, 2012).

Moreover, e-banking tools can also facilitate the process of increasing financial literacy among the low- to moderate-income households. Those who prefer the Internet to human financial planners to solve their financial concerns are more likely to be young and less wealthy (Son, 2012). Compared to the traditional do-it-yourself (DIY) investors, those who utilized robo-advisors spent less time researching and experienced lower investment flexibility. On the other hand, compared to human financial advisors' clients, robo-advisor users had lower costs and lower minimum investment requirements (Ludwig, 2018).

Huxley and Kim (2016) examined four robos, Betterment, Motif, Schwab, and Wealthfront, and found that most of the portfolios generated by these robos, based on a moderately risk-tolerant user, were focused on short-term returns (an average of 3–5 years) rather than long-term accumulations. Moreover, they also found that the average user's age was late 30s to early 40s, which meant that most of them were in need of a long-term investment strategy for retirement. There may exist a mismatch between the robo-advisors' recommendations based on simple questionnaires collected from users and the actual investment needs and goals of these users, which often comprise more complex financial situations, constraints, and psychological perspectives that can hardly be captured by robos.

Theoretically speaking, a systematic framework or theory is lacking to understand robo-advisor utilization behavior. Since robo-advisors are technology-based financial advisory platforms, utilization behavior may require a certain level of technology literacy (such as smartphones, Internet, tablets, etc.). Therefore, technology adoption theories may also be applied to robo-advisor adoption behaviors. The diffusion of innovations (DOI) theory developed by Rogers (1962) provides theoretical support for this current study. This theory has been utilized in research on fintech and financial digitalization, such as virtual banking adoption (e.g., Frame & White, 2014; Suoranta & Mattila, 2004), and retail payment and e-commerce (e.g., Szmigin & Foxall, 1998); however, it has not been rigorously employed in the emerging area of robo-advisors. Rogers (1962) also proposed socioeconomic characteristics of these technology adopters. For instance, no age difference was found between early adopters and later adopters. However, the early adopters were more likely to be literate, have higher social status, and have favorable attitudes toward borrowing and credit compared to later adopters. Additionally, the early adopters exposed themselves to more interpersonal communication channels and were more active in seeking information.

The innovation adoption process developed by Rogers (1962) states that actual behavior may be caused by numerous factors and motivations that stem from different branches of a decision tree. This study aims to examine these factors and motivations from an information search perspective. The information search model developed by Beales et al. (1981) categorizes information search into internal and external sources. Specifically, this model posits that consumers may acquire information using internal sources, such as previous memory and prior experience; and external information sources, such as "third-party consultants, seller-controlled sources, and direct inspection," when making a decision to acquire or use a new product or service. Since it is easier to retrieve memories, people tend to use their internal sources first, in which step they actively search and weigh the benefit and cost associated with a behavior or choice. When necessary, consumers also seek external sources to gather information. Researchers recently adapted Beales et al.'s (1981) information search model in a study of household borrowing behavior (Fan & Chatterjee, 2017). Following the information search models, they included financial knowledge, human capital (including educational attainment and perceived and objective financial knowledge), and risk tolerance into internal information sources. Further, influential external sources in consumers' borrowing behavior includes financial advice provided by financial experts. Their results indicated that seeking external financial help and most of the internal information sources were positively associated with credit-comparing behavior. Along this line, Huang, Lassu, and Chan (2018) examined the relationship between financial well-being, self-efficacy, information source attributes, and the information sources selection, and whether the chosen sources can provide what is needed for millennials. Moreover, an Indian study showed that seeking help, having greater financial knowledge, and using electronic banking are positively associated with young adults' financial management behavior (Bapat, 2019).

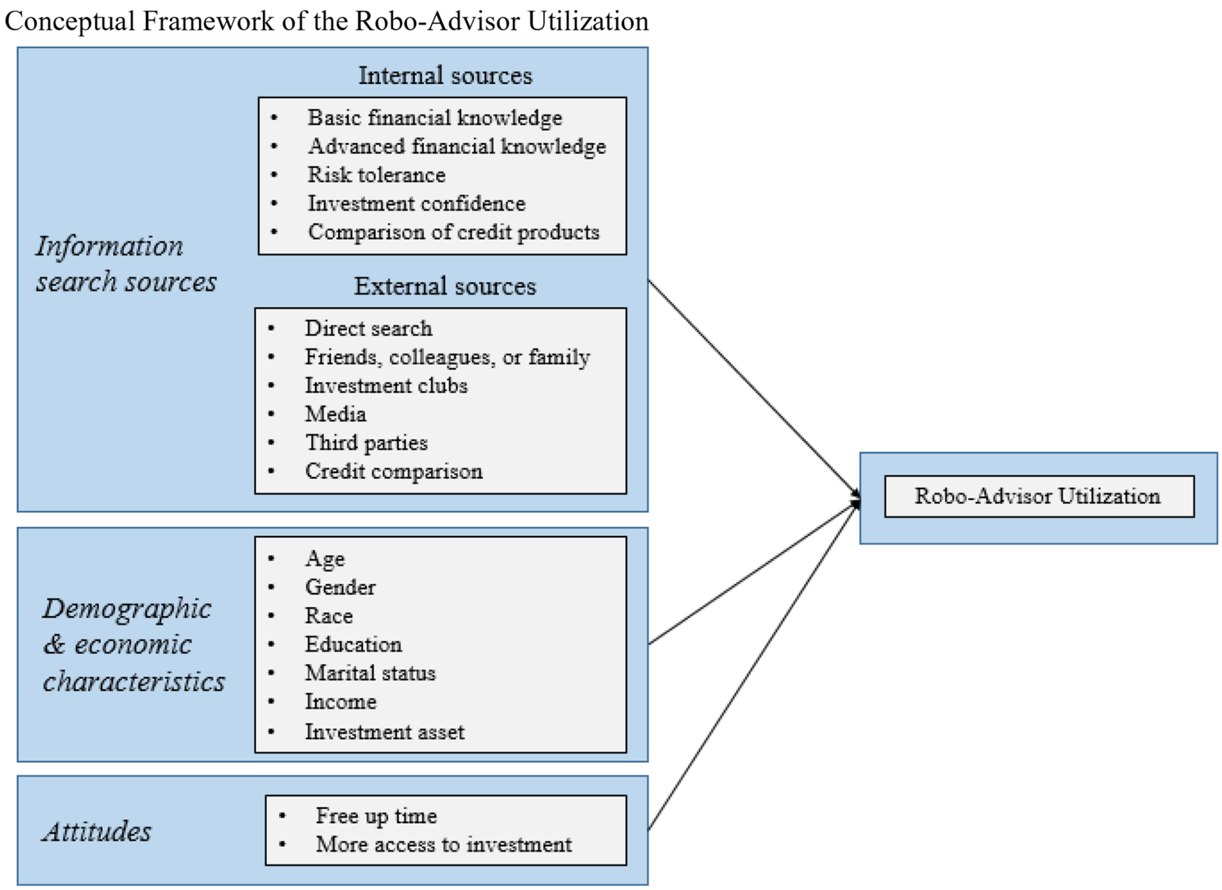
A series of studies has indicated that financial knowledge and literacy have a positive influence on financial capability and behavior (Fan & Chatterjee, 2018; Lusardi, 2008; Xiao, Chen, & Chen, 2014). The measures of financial knowledge and literacy can further be divided into basic and advanced levels (Lusardi, 2008). Lusardi (2008) identified three questions developed by Lusardi and Mitchell (2007) for the Health and Retirement Study as basic measures of financial literacy. These three questions tend to measure respondents' fundamental understanding of economic concepts (compound and inflation), basic numeracy level, and knowledge of investment risk diversification. Advanced literacy, on the other hand, measures respondents' more comprehensive understanding of personal finance, including concepts such as mutual funds, stocks, and bonds (van Rooij, Lusardi, & Alessie, 2011). Other internal factors, such as risk tolerance and financial confidence, were also found to significantly affect external information-seeking behavior and financial decisions. For example, Joo and Grable (2001) found that those with higher risk tolerance were more likely to seek external financial help from financial professionals.

Conceptual Framework and Hypotheses

Based on the literature, the DOI theory, and information search models, we propose a conceptual framework (see Figure 1) that illustrates the potential relationships between internal and external information sources, attitudinal factors associated with seeking advice from financial advisors, and demographic and socioeconomic controls that have been associated with seeking professional financial advice in previous literature. According to the LendEDU report (Hamory, 2018), attitudes toward the utilization of robo-advisor-based services may significantly affect how individuals evaluate robos' usefulness for investment and wealth accumulation. The implicit and unconscious attitude would also affect whether or how to search for information related to robos. Based on Beales et al.'s (1981) information search sources and Lusardi's (2008) categorization of financial literacy, the internal information sources in the current study include basic and advanced financial and investment knowledge, perceived financial knowledge, risk tolerance, and investment confidence. The external sources include all possible sources of investment information, including direct search, information from family and friends, investment clubs, and third parties (brokers and wealth managers, regulatory sources, employers, etc.). As suggested by Fan and Chatterjee (2017), financial knowledge, objective financial knowledge, and risk tolerance can be considered internal information search sources. In this study, we added attitudes toward using financial advisors including saving time and creating access to more investments in order to explore whether these perceptions of financial advisory services can motivate the adoption of robo-advisory services.

Since Rogers (1962) pointed out that early technology adopters tend to engage in interpersonal communication and show a positive attitude toward credit and borrowing, we therefore also propose that those who actively search for and compare credit are also likely to utilize the robo-advisor services. In addition, based on the demographic profile of the early technology adopters (Huxley & Kim, 2016; Rogers, 1962), we propose that robo-advisor adopters are relatively young, more financially sophisticated, engage in more external information search activities, and enjoy

Figure 1. Conceptual framework of the robo-advisor utilization.



a higher socioeconomic status. The following hypotheses were proposed based on the conceptual framework outlined above.

> **H1:** Internal information sources related to investment are positively associated with the adoption of robo-advisors after controlling for attitudinal factors, external information sources, and socioeconomic and demographic characteristics.
>
> **H2:** External information sources related to investment are positively associated with the adoption of robo-advisors after controlling for attitudinal factors, internal information sources, and socioeconomic and demographic characteristics.
>
> **H3:** Attitudes toward general financial advisors are positively associated with the adoption of robo-advisors after controlling for other internal and external search factors and socioeconomic and demographic characteristics.

Methods

Data

This article used data from the 2015 wave of the state-by-state National Financial Capability Study (NFCS) and its Investor Survey (IS) supplement. The NFCS dataset is funded and maintained by the Financial Industry Regulatory Authority (FINRA). The dataset was developed in collaboration with the U.S. Department of the Treasury and the President's Advisory Council on Financial Literacy (Mottola & Kieffer, 2017). The 2015 wave of the NFCS dataset included 27,564 respondents. The IS supplement was constructed using respondents in the 2015 NFCS who reported owning investments outside of their retirement plans, and included detailed information on the investment behavior, attitude, and decision-making of these respondents (Mottola & Kieffer, 2017). The 2015 IS supplement included

2,000 respondents. This supplemental dataset was merged with the 2015 state-by-state NFCS to obtain detailed information related to investment-related attitude, knowledge, decision, behavior, and general financial literacy and other sociodemographic characteristics of the investor survey participants. After dropping the "Don't know" and "Prefer not to say" responses from the merged data, this study includes 1,949 respondents who reported having investments in non-retirement accounts and who participated in the household financial decision-making process.

Dependent Variables

The dependent variable was whether the respondents had used the services provided by a robo-advisor. This variable was constructed based on a question in the 2015 IS supplement: *"Have you ever used an automated financial adviser that provides investment advice and makes trades on your behalf?"* The variable was coded as 1 if the respondents answered "Yes," and the variable was coded as 0 if the respondents answered "No." The "Don't know" and "Prefer not to say" variables were dropped from the analyses.

Independent Variables

The independent variables included internal, external, and attitudinal factors related to the respondents' information search and utilization behaviors and their socioeconomic and demographic characteristics. These variables are explained below.

Internal Information Sources. One of the independent variables of interest in this study included the measures of financial and investment knowledge. Following the two levels of financial knowledge measure in the literature (Lusardi, 2008; Lusardi & Mitchell, 2007; van Rooij et al., 2011), we created two separate sets of financial knowledge variables: basic financial knowledge and advanced investment knowledge. Each set included objective and subjective dimensions. The objective basic financial knowledge was constructed using six basic financial literacy questions developed by Lusardi and Mitchell (2007) that were included in the 2015 state-by-state NFCS dataset, measuring respondents' fundamental knowledge of interest, inflation, risk, and numeracy, and so forth. (survey questions are available from the FINRA Investor Education Foundation website). Responses to each of the six questions were coded as 1 for a correct answer and as 0 for an incorrect or "Don't know" answer. Then, the six responses were added up to construct the basic objective financial knowledge score. The 2015 IS supplement also included additional questions that were more focused on investment-related knowledge, such as respondents' understanding of buying on margin, short selling, historic market returns, different asset classes, and so forth (survey questions are available from the FINRA IEF website). An advanced objective investment knowledge variable was constructed using responses from the 10 investment-related questions. The responses to each of the 10 questions were coded as 1 if answered correctly and as 0 for an incorrect or "Don't know" response. The respondents were also asked about their subjective or perceived financial and investment knowledge. The basic and advanced subjective knowledge variables of general finance and investment were coded based on self-reported answers on a 1–7 scale (1 = *Very low;* 7 = *Very high*). Specifically, the basic perceived financial knowledge question used in the survey was, "*On a scale from 1 to 7 . . . how would you assess your overall financial knowledge*?"; whereas the perceived level of advanced investment knowledge was, "*On a scale from 1 to 7 . . . how would you assess your overall knowledge about investing?*" The investor confidence scale was constructed based on a question where the respondents were asked how comfortable they felt about making investment decisions. These responses were recorded on a 1–10 scale (where 1 = Least comfortable; 10 = Very comfortable). Investors were also asked whether they searched for information and compared credit cards before deciding upon one. This ability to compare and comprehend sophisticated credit-related information was also included as an internal source and was coded as binary (1 = Yes; 0 = No). The investor risk tolerance scale was included as an internal source and was reversely coded on a 1–4 scale (the original scale before reverse coding: 1 = *Take substantial financial risks expecting to earn substantial returns;* 4 = *Not willing to take any financial risk*).

External Sources. The external sources of information variables were constructed based on the participants' responses to questions regarding the types of information sources that they may have used for investment decision-making. The binary investment information search variables included (a) direct search for information on the company the respondents were investing in, such as annual reports and company websites (1 = Yes; 0 = No); (b) seeking investment information from family, friends, and colleagues (1 = Yes; 0 = No); (c) obtaining financial information from the media, such as TV, radio, newspapers, magazines, and online financial information (1 = Yes; 0 = No); (d) receiving investment information from investment clubs or membership organizations (1 = Yes; 0 = No); and (e) receiving information from third-party sources, such as brokers, advisors, employer-based information, industry regulators, mutual funds, or other financial services intermediaries (1 = Yes; 0 = No).

Attitudinal Factors. The attitudinal factors included in the model reflected important reasons people may use financial advisors and potential motivations for adopting robo-advisors. These variables were constructed based on a question in the IS supplement where the respondents were asked what factors were important in their decisions to adopt the services of a financial advisor. The first variable included in this study was "to free up time" (1 = Very important or somewhat important; 0 = Not important), and the second variable was "to have access to investments I couldn't get on my own" (1 = Very important or somewhat important; 0 = Not important).

Sociodemographic Characteristics. The sociodemographic variables included in this study were based on the association of these variables with information search, technology adoption, and investment decisions and behaviors, as documented in the literature. The variables include controls for age, gender, educational attainment, race/ethnicity, marital status, income, and net value of investment assets in non-retirement accounts (Chang, 2005; Elmerick, Montalto, & Fox, 2002; Son, 2012).

Analyses

Multivariate analyses were used to empirically test the proposed hypotheses in this study. To assess the relative contributions of the internal and external investment information sources, attitudinal factors, and demographic factors associated with the adoption of robo-advisors, a step-wise regression was first estimated.

$Y = f\ (I, E, A, D)$

Where Y = Utilization of robo-advisors (1 = Yes; 0 = No)

I = Vector of internal information search sources

E = Vector of external information search sources

A = Vector of attitudinal factors

D = Vector of demographic and socioeconomic variables

Next, we used a restricted logistic regression model to examine the likelihood of adopting robo-advisors when controlling for age, marital status, educational attainment, income, risk tolerance, investment knowledge, and investable assets using a logit model. The purpose of this additional analysis was to examine whether age, when interacted with risk tolerance, investment knowledge, income, and investable assets, was significantly associated with the adoption of robo-advisors. This model was estimated as a robustness test for the empirical analyses of this article. In the restricted model, the age variable was collapsed to three levels: 3 = 65 or older, 2 = 35–64, and 1 = 18–34. In this model, the reference group was the 65 or older cohort. Similarly, the educational attainment variable was coded as college or higher (1 = Yes; 0 = No), and the marital status variable was coded as married (1 = Yes; 0 = No). The income variable was also collapsed to two levels and was coded as "1" if the income was in the top third of all respondents in the survey (income $100,000) and as "0" otherwise. Similarly, ownership of investable assets of $250,000 or more was coded as "1" if the amount held in investable assets was in the top 33% of all respondents in the survey and as "0" otherwise.

Results

Descriptive Statistics

The descriptive statistics of the sample are presented in Table 1. In this study, 13.19% of the respondents had used robo-advisor based platforms. Further, 63.25% of the respondents mentioned they would utilize the services of a financial advisor to free up time, and 84% mentioned that they would like to utilize the services of a financial advisor to have access to a greater number of investment-related products. On average, the respondents answered 4.24 of the 6 basic financial knowledge questions correctly and 4.66 of the 10 advanced investment questions correctly. On a scale of 1–7, the perceived level of basic financial knowledge was 5.78, while the perceived advanced investment knowledge was 4.85. The average score of the self-reported comfort with making investment decisions was 7.09 out of 10. Of all the respondents, 43.85% reported searching for and comparing credit-related information before they applied for a credit card.

Among the external resource-related factors, 70.62% of respondents received investment-related information through their employers, 47.47% received investment-related information from family members, and 15.21% received information through investment clubs. 87.70% of the respondents received investment information through third-party sources like reports, brochures, newsletters, brokerage firms, mutual fund companies, and other financial services companies. About 45.70% reported receiving investment information from media.

Women comprised 44.95% of the sample, and Whites comprised 80.03% of respondents. In this study, 89.05% of the respondents had educational attainment of some college or higher and 68.5% of the respondents were married. In terms of income, 21% of the respondents had an income of \$50,000 or less, while around 34% of the respondents had a household income of \$100,000 or more. Similarly, over half the sample (51.51%) had investable assets of \$100,000 or more.

Factors Associated With the Adoption of Robo-Advisors

Table 2 shows the results of the step-wise logistic regression to determine the factors associated with respondents' adoption of robo-advisors. The control variables included internal information sources, external information sources, attitudinal factors, and the sociodemographic variables. Based on the importance of association of the variables with the likelihood of adopting robo-advisors, the step-wise model fitted the variables (at 5% level of significance) in the following order: internal information sources, external information sources, sociodemographic factors, and attitudinal factors.

The internal information factors related to subjective basic financial knowledge (odds = 1.533; $p < .001$), advanced investment knowledge (odds = 1.224; $p < .01$), investment risk tolerance (odds = 1.981; $p < .001$), and the practice of comparing credit cards (odds = 2.016; $p < .001$) were positively associated with the likelihood of adopting robo-advisors. Conversely, objective basic financial knowledge (odds = 0.865; $p < .001$) and advanced investment knowledge (odds = 0.804; $p < .001$) were negatively associated with the likelihood of adopting robo-advisors.

The external information factors were fitted in the next model. Obtaining information through participating in investment clubs and organizations (odds = 2.811; $p < .001$), applying third-party sources (odds = 2.045; $p < .05$), and using media (odds = 1.408; $p < .05$) were positively associated with the adoption of robo-advisors.

Among sociodemographic factors, ownership of investable assets worth \$500,000 or more (odds = 3.795; $p < .01$) was positively associated with the adoption of robo-advisors. Conversely, being single (odds = 0.629; $p < .01$), having an income of \$100,000 or more, and being over 65 (odds = 0.193; $p < .001$) were negatively associated with the adoption of robo-advisors. The need to save time (odds = 1.864; $p < .001$) was the sole attitudinal factor positively associated with the adoption of robo-advisors.

The Determinants of Using Robo-Advisors Using Interaction Models

Table 3 shows the results for the likelihood of utilizing robo-advisors after controlling for the interactions of age with financial knowledge, risk tolerance, income, and investable assets. The results indicated that compared to individuals 65 or older, younger individuals (ages 18–34 and 35–64) were more likely to adopt robo-advisors. Investor risk tolerance and subjective investment knowledge were also positively associated with the likelihood of using robo-advisors. The results of the interaction terms indicated that, compared to the reference group of individuals aged 65 or older, younger individuals (18–34 and 35–64) with higher subjective investment knowledge and higher risk tolerance were significant and positively associated with the utilization of robo-advisors. Additionally, respondents between 35 and 64 years of age with higher amounts of investable assets were positively associated with the utilization of robo-advisors.

Discussion

The results of our study confirmed that internal search sources (H1), external search sources (H2), and one attitudinal factor (H3), were significantly associated with the investors' adoption of robo-advisory services. Among the internal search factors subjective basic financial knowledge (X^2= 16.19; $p < .001$) and subjective investment knowledge (X^2= 33.20; $p < .001$) were both significantly associated with the utilization of robo-advisors. Among the external search factors participation in investment clubs (X^2= 22.82; $p < .001$) had the highest odds of working with robo-advisors. Within the attitudinal factors, freeing up time (X^2= 14.28;

TABLE 1. Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
Use Robo Advisors	13.19%		0	1
Attitudes				
Free time	63.25%		0	1
More access	84.00%		0	1
Internal Information Sources				
Basic financial knowledge				
Subjective	5.78	0.916	2	7
Objective	4.24	1.460	0	6
Advanced Investment Knowledge				
Subjective	4.86	1.394	1	7
Objective	4.66	2.227	0	10
Investment risk tolerance	2.40	0.795	1	4
Investment confidence	7.09	1.969	1	10
Comparing credit cards	43.85%		0	1
External Information Sources				
Company information	70.62%		0	1
Family, friends, colleagues	47.47%		0	1
Investment clubs and organizations	15.21%		0	1
Third Parties	87.70%		0	1
Media	45.70%		0	1
Socioeconomic and Demographic Characters				
Age				
18–24	3.20%		0	1
25–34	12.95%		0	1
35–44	14.30%		0	1
45–54	17.30%		0	1
55–64	22.25%		0	1
65+	30.00%		0	1
Gender				
Male	55.05%			
Female	44.95%		0	1
Race/ethnicity				
White	80.30%		0	1
Non-White	19.70%			
Education				
High school or less	10.95%		0	1
Some college	28.05%		0	1
College	34.75%		0	1
Postgraduate	26.25%		0	1

(*Continued*)

TABLE 1. Descriptive Statistics *(Continued)*

Variable	Mean	Standard Deviation	Min	Max
Marital Status				
Married	68.55%		0	1
Single	18.00%		0	1
Separated/divorce	8.95%		0	1
Widowed	4.50%		0	1
Income Levels				
<$50,000	21.00%		0	1
$50,000–75,000	23.50%		0	1
$75,000–$100,000	21.15%		0	1
$100,000–$150,000	21.00%		0	1
$150,000+	13.35%		0	1
Investable Asset Value				
<$10,000	20.00%		0	1
$10,000–$50,000	14.65%		0	1
$50,000–$100,000	14.25%		0	1
$100,000–$250,000	18.85%		0	1
$250,000–$500,000	15.11%		0	1
$500,000+	17.55%		0	1

$p < .001$) was positively associated with the utilization of robo-advisor services.

The significant association between freeing up time and the utilization of robo-advisors ties well with previous studies where Ludwig (2018) found that people who utilized robo-advisors were less likely to spend time searching for investment-related information. Additionally, in previous studies, the users of robos have reported the ease and convenience of using robos as being important factors in their decisions to utilize these services (e.g., Brown, 2017; Salo, 2017. Among the internal search sources, perceived or subjective investment knowledge was positively associated with the adoption of robo-advisors, but objective investment and financial knowledge were negatively associated with the utilization of robo-advisors. The subjective investment knowledge variable was significant in the step-wise logistic regression model and in the restricted interaction model. Additionally, subjective investment knowledge when interacted with age groups 64 or younger was also significantly associated with the utilization of robo-advisors. In previous studies, subjective knowledge has been associated with responsible financial behavior (Perry & Morris, 2005). The negative association between objective financial and investment knowledge with the adoption of robo-advisors was surprising. Ludwig (2018) found that traditional DIY investors have different characteristics from those investors who are early adopters of robo-advisory platforms. It is possible that those who are more knowledgeable, in terms of both general finance and investment, are more likely to prefer either to work with a human advisor or to manage investments on their own and have therefore refrained from delegating their portfolio management decisions to robo-advisor-based platforms. More research is necessary to better understand this negative association between objective investment and financial knowledge and the adoption of robo-advisors.

This study found that investment risk tolerance was positively associated with the adoption of robo-advisors. Risk tolerance was found significant in both the step-wise logistic regression model (Table 2) and in the restricted interaction model (Table 3). Additionally, the interaction of risk tolerance and being 64 or younger were also significant and positively associated with the utilization of using robo-advisors. Risk tolerance has been previously associated with financial advice-seeking behavior (Gerrans & Hershey, 2017; Joo & Grable, 2001). It is possible that individuals with

TABLE 2. Step-Wise Regression

Variable Type	Variable Name	Odds.	*SE*	Sig.
Internal Information Sources	Basic financial knowledge			
	Subjective	1.533	0.198	***
	Objective	0.865	0.051	***
	Advanced investment knowledge			
	Subjective	1.224	0.069	**
	Objective	0.804	0.063	***
	Risk tolerance	1.981	0.281	***
	Investment confidence	1.074	0.098	
	Comparing credit cards	2.016	0.392	***
External Information Sources	Company information	0.701	0.174	
	Family, friends, colleagues	0.693	0.141	
	Investment Club	2.811	0.638	***
	Third Parties	2.045	0.534	*
	Media	1.408	0.097	*
Sociodemographic Controls	Age (ref: 18–24)			
	25–34	0.822	0.376	
	35–44	0.909	0.429	
	45–54	0.563	0.281	
	55–64	0.501	0.249	
	65+	0.193	0.099	***
	Gender (ref: Male)			
	Female	0.822	0.178	
	Race/ethnicity (ref: Non-White)			
	White	0.912	0.201	
	Education (ref: College)			
	High school or less	1.301	0.578	
	Some college	0.751	0.184	
	Postgraduate	1.211	0.306	
	Marital status (ref: Married)			
	Single	0.629	0.144	**
	Separated/divorce	1.011	0.418	
	Widowed	2.273	1.385	
	Income levels (ref: <$50,000)			
	$50,000–75,000	0.681	0.208	
	$75,000–$100,000	0.749	0.235	
	$100,000–$150,000	0.398	0.136	***
	$150,000+	0.299	0.123	***

(*Continued*)

TABLE 2. Step-Wise Regression *(Continued)*

Variable Type	Variable Name	Odds.	*SE*	Sig.
	Investable asset value (ref:<$10,000)			
	$10,000–$50,000	1.163	0.562	
	$50,000–$100,000	1.191	0.593	
	$100,000–$250,000	1.351	0.479	
	$250,000–$500,000	1.337	0.509	
	$500,000+	3.795	0.557	**
Attitudes	Free time	1.864	0.307	***
	More access	1.105	0.501	
	Intercept	0.134	0.001	***

Note. *SE* = standard error.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

TABLE 3. Interaction Terms Using the Restricted Model

	Odds	*SE*	Sig
Age (Ref: Age 65 or higher)			
Age 18–34	1.427	0.584	**
Age 35–64	1.509	0.698	**
Education (Ref:<College)			
College or more	1.110	0.197	
Married	1.172	0.213	
Risk tolerance	2.484	1.030	**
Objective Inv. Knowledge	0.605	0.888	
Subjective Inv. Knowledge	1.852	0.476	***
High Income (Upper 33%)	1.149	0.712	
High Investable Assets (Upper 33%)	1.227	0.416	**
Age 18–34 × Risk Tol	1.116	0.419	***
Age 35–64 × Risk Tol	1.820	0.361	***
Age 18–34 × Subj. Inv Knowledge	1.015	0.295	***
Age 35–64 × Subj Inv Knowledge	1.289	0.360	***
Age 18–34 × Obj Inv Knowledge	1.335	0.823	
Age 35–64 × Obj. Inv Knowledge	1.306	0.991	
Age 18–34 × High Income	0.300	0.217	
Age 35–64 × High Income	0.507	0.335	
Age 18–34 × High Assets	0.755	0.895	
Age 35–64 × High Assets	1.856	0.477	***
Intercept	0.001	0.002	***

Note. *SE* = standard error.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

a higher risk tolerance face lower anxiety when adopting robo-advisory platforms, which are still in their early stages of existence in the fintech era, as they seek financial advice compared to those individuals with lower risk tolerance. This study found that researching credit card information before applying for a card was positively associated with utilizing the services of a robo-advisor. This confirmed the proposition that a favorable attitude toward credit is positively correlated with the early adoption of technologies in the DOI theory (Rogers, 1962).

Among external sources of information, participation in investment clubs and organizations and the information received from media and third-party sources, such as brokers, other financial intermediaries, and workplace, were positively associated with the utilization of robo-advisor services. It is possible that people who interacted with peers through investment clubs or received investment information exposure from third-party sources were better informed on the availability and existence of robo-advisory platforms, and hence they were more likely to be the early adopters of robos. It is also possible that the respondents could have received information through multiple sources. The sources investigated in this study were not mutually exclusive, but several of the external information sources were significantly associated with the adoption of robo-advisors. These findings underscored the importance of access to external information sources on the adoption of robo-advisors.

The interactions of age groups younger than 65 with subjective investment knowledge and with investor risk tolerance were positively associated with the utilization of robo-advisors. It should be noted that the age variables were collapsed to three levels in the restricted model with interaction terms (Table 3). However, these were not applied to the step-wise logistic regression model. This is one of the reasons that the test results for the age variables differed between the step-wise logistic regression and the restricted interaction term models. Overall, findings of this study corroborated the findings from the Huxley and Kim (2016) and Son (2012) studies and confirmed that the younger age groups were more likely to utilize robo-advisors. Additionally, the positive relationships of risk tolerance and subjective investment knowledge on the adoption of robos informed the emerging literature on the determinants of individuals' adoption and utilization of automated investment platforms.

The significant relationship between investable assets and the robo-advisor utilization provided economic significance for the financial services industry in general and for the financial planning profession in particular. Ownership of investable assets of $500,000 or more was positively associated with the adoption of robo-advisors in the step-wise logistic regression model, and the ownership of $250,000 or higher in investable assets was significantly associated with the adoption of robo-advisors in the restricted interaction model. Additionally, the investable assets variable, when interacted with the 35–64 age group, was significantly associated with the adoption of robo-advisors in the restricted interaction model. The significance of investable assets also indicated an opportunity for financial planners to integrate automated investment platforms within their overall comprehensive planning practices as a way to further expand business. These findings are also encouraging for emerging fintech platforms, which position themselves as disrupters to the traditional financial services industry. The finding also has implications for retirement plan administrators and other financial institutions that work with retirement plans. The integration of robo-advisor platforms could simplify asset allocation decisions for the plan participants by providing a low-risk, low cost, and low-effort default approach for fund selection and allocation (Agnew & Szykman, 2005; McKenzie, Liersch, & Finkelstein, 2006).

More research is also needed for understanding why single and high-income individuals were less likely to utilize the services of robo-advisors. One possibility is that the single and high-income individuals are risk takers and prefer riskier investments such as stocks, alternative asset classes, or other undiversified investment opportunities. Future studies need to focus on this important demographic group to better understand the reason behind the lower likelihood of this group for participation in robo-advisor based services.

There were several limitations of this study as it explored the antecedents of the adoption of robo-advisors from the perspective of attitudinal factors and sources of information search among individuals. The survey was limited to participants who already had investable assets, and therefore the participants overall were wealthier, had higher income, higher educational attainment, and were more likely to be financially sophisticated. Another limitation of this study is that the NFCS data used in this study and the IS supplement are cross-sectional in nature. More research with panel data, when available, will provide greater insights into the decision-making process of individuals when examining the adoption of robo-advisor-based investment platforms.

Another limitation is the possible sample bias, since younger investors have more opportunities to access this new emerging technology of robo-advisory platforms than older ones. Many older investors may be less familiar with these technology-based investment platforms because they did not have the opportunity to access or use these services during the wealth formation and accumulation phases of their life cycle and are therefore more comfortable with using traditional, human-involved brokerage services.

Some potential issues with robo-advisors, although not directly examined in this study, should be considered by potential users when they make adoption decisions and by financial practitioners and firms when making decisions to provide hybrid services that incorporate robos with a human touch. For example, Fein (2015) questioned the investment recommendations provided by robo-advisors, and some robo-advisors may not have registered as investment companies. Undoubtedly, regulatory supervision and guidance are needed to improve the overall robo-advisory platforms and practice, including but not limited to the areas of concerns, such as fiduciary versus suitability standards, fees and cost transparency, potential conflicts of interest disclosure, assumptions and limitations of algorithms, and so forth. The other challenge of robo-advisory platforms lies in the reliability and validity of the questionnaires used to collect user information (Fein, 2015; Huxley & Kim, 2016; Kaya, 2017). The oversimplified information collection process may cause a mismatch between the actual financial needs and the recommended portfolio management. Some psychological and attitudinal factors, such as money beliefs, prior investment experience, and preferences for socially responsible investing, can hardly be retrieved and quantified using the current robo-advisor algorithms.

Implications

The findings of this study provide implications for financial planners and scholars of financial counseling and planning. The results suggest that the investors who are early adopters of robo-advisor services are less likely to be older (65 or older) but are more likely to possess higher amounts of investable assets, higher perceived investment knowledge, and be more risk tolerant when investing. The individuals who are time constrained but who actively engage in obtaining investment-related information through participation in investment clubs and through third-party sources, and those who carefully shop for credit cards, are more likely to utilize the services of a robo-advisor. This study finds that working-age investors are more likely to use robo-advisor services.

Many scholars and professionals in the financial services industry view robo-advisors favorably as being able to lower the entry-level barriers to professional financial advice, which might be beneficial for investors of modest means who are trying to save for their retirement (Ludwig, 2018; Servon & Kaestner, 2008; Son, 2012). However, the findings of our study indicate the opposite: The current adopters who utilized robo-advisors were investors with substantial investable assets. The results of our study indicate that robo-advisors do not currently appear to be widely used by a vast cohort of the U.S. population: the baby boomers, who are currently entering retirement. Future research is necessary to further understand the factors that can popularize the robo-advisor platforms for those who may potentially benefit from adopting this technology for investment.

References

Agnew, J. R., & Szykman, L. R. (2005). Asset allocation and information overload: The influence of information display, asset choice, and investor experience. *The Journal of Behavioral Finance*, *6*(2), 57–70. https://doi.org/10.1207/s15427579jpfm0602_2

Bapat, D. (2019). Exploring antecedents to financial management behavior for young adults. *Journal of Financial Counseling and Planning*, *30*(1), 44–55. https://doi.org/10.1891/1052-3073.30.1.44

Beales, H., Mazis, M. B., Salop, S. C., & Staelin, R. (1981). Consumer search and public policy. *Journal of Consumer Research*, *8*(1), 11–22. https://doi.org/10.1086/208836

Brown, M. (2017, September 19). *Robo advisors vs. financial advisors-Millennials still prefer real-life*. *LendEDU*. Retrieved from https://lendedu.com/blog/robo-advisors-vs-financial-advisors/

Chang, M. L. (2005). With a little help from my friends (and my financial planner). *Social Forces*, *83*(4), 1469–1497. https://doi.org/10.1353/sof.2005.0061

Collins, J. M. (2012). Financial advice: A substitute for financial literacy? *Financial Services Review*, *21*(4), 307–322. https://doi.org/10.2139/ssrn.2046227

Elmerick, S. A., Montalto, C. P., & Fox, J. J. (2002). Use of financial planners by U.S. households. *Financial Services Review*, *11*(3), 217–231.

Fan L 2017 *The influences of financial help-seeking and other information sources on consumer's financial management behavior*. Doctoral dissertation. Retrieved from https://www.libs.uga.edu/etd. University of Georgia, Athens, GA.

Fan, L., & Chatterjee, S. (2017). Borrowing decision of households: An examination of the information search process. *Journal of Financial Counseling and Planning*, *28*(1), 95–106. https://doi.org/10.1891/1052-3073.28.1.95

Fan, L., & Chatterjee, S. (2018). Application of situational stimuli for examining the effectiveness of financial education: A behavioral finance perspective. *Journal of Behavioral and Experimental Finance*, *17*, 68–75. https://doi.org/10.1016/j.jbef.2017.12.009

Fein, M. L. (2015). *Robo-advisors: A closer look. SSRN Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2658701

Finke, M. S., Huston, S. J., & Waller, W. (2009). Do contracts impact comprehensive financial advice? *Financial Service Review*, *18*(28), 177–194. https://doi.org/10.2139/ssrn.1429807

Frame, W. S., & White, L. J. (2014). Technological change, financial innovation, and diffusion in banking. In A. N. Berger, P. Molyneux, & J. O. S. Wilson (Eds.), *The Oxford handbook of banking* (p. 271). New York, NY: Oxford University Press.

Gerrans, P., & Hershey, D. A. (2017). Financial adviser anxiety, financial literacy, and financial advice seeking. *Journal of Consumer Affairs*, *51*(1), 54–90. https://doi.org/10.1111/joca.12120

Hamory, J. (2018, January 17). *Robo-advisors encouraging millennials to invest, but do they understand how it works? LendEDU*. Retrieved from https://lendedu.com/blog/robo-advisors-attracting-millennials/

Hanna, S. D., & Lindamood, S. (2010). Quantifying the economic benefits of personal financial planning. *Financial Services Review*, *19*(2), 111–127.

Huang, E. J., Lassu, R. A., & Chan, K. K. (2018). User-source fit and financial information source selection of millennials. *Journal of Financial Counseling & Planning*, *29*(2), 272–289. https://doi.org/10.1891/1052-3073.29.2.272

Huxley, S. J., & Kim, J. Y. (2016). The short-term nature of robo portfolios. *Advisor perspectives*. Retrieved from https://www.advisorperspectives.com/articles/2016/09/12/the-short-term-nature-of-robo-portfolios

Joo, S. H., & Grable, J. E. (2001). Factors associated with seeking and using professional retirement-planning help. *Family and Consumer Sciences Research Journal*, *30*(1), 37–63. https://doi.org/10.1177/1077727X01301002

Kaya, O. (2017). *Robo-advice–a true innovation in asset management. Deutsche bank research*. Retrieved from https://www.dbresearch.com/

Kim, J., Garman, E. T., & Sorhaindo, B. (2003). Relationships among credit counseling clients' financial wellbeing, financial behaviors, financial stressor events, and health. *Journal of Financial Counseling and Planning*, *14*(2), 75–87.

Kitces, M. (2018, October 29). *How "robo" technology tools are causing fee deflation but not fee compression. Nerd's Eye View at Kitces.com*. Retrieved from https://www.kitces.com/blog/fee-compression-fee-deflation-robo-advisor-cost-savings-productivity-efficiency/

Ludwig, L. (2018, November 7). *The rise of the robo advisors - Should you use one? Investor Junkie*. Retrieved from https://investorjunkie.com/35919/robo-advisors/

Lusardi, A. (2008). *Financial literacy: An essential tool for informed consumer choice?* CFS working paper, No. 2008/19. Retrieved from http://nbn-resolving.de/urn:nbn:de:hebis: 30-56927

Lusardi, A., & Mitchell, O. S. (2007). Financial literacy and retirement preparedness: Evidence and implications for financial education. *Business Economics*, *42*(1), 35–44. https://doi.org/10.2145/20070104

Marsden, M., Zick, C. D., & Mayer, R. N. (2011). The value of seeking financial advice. *Journal of Family and Economic Issues*, *32*(4), 625–643. https://doi.org/10.1007/s10834-011-9258-z

McKenzie, C. R., Liersch, M. J., & Finkelstein, S. R. (2006). Recommendations implicit in policy defaults. *Psychological Science*, *17*(5), 414–420. https://doi.org/10.1111/j.1467-9280.2006.01721.x

Moreland, K. A. (2018). Seeking financial advice and other desirable financial behaviors. *Journal of Financial Counseling & Planning*, *29*(2), 198–207. https://doi.org/10.1891/1052-3073.29.2.198

Mottola, G. R., & Kieffer, C. N. (2017). Understanding and using data from the national financial capability study. *Family and Consumer Sciences Research Journal*, *46*(1), 31–39. https://doi.org/10.1111/fcsr.12227

Perry, V. G., & Morris, M. D. (2005). Who is in control? The role of self–perception, knowledge, and income in explaining consumer financial behavior. *Journal of Consumer Affairs*, *39*(2), 299–313. https://doi.org/10.1111/j.1745-6606.2005.00016.x

Phoon, F., & Koh, F. (2017). Robo-advisors and wealth management. *The Journal of Alternative Investments*, *20*(3), 79–94. https://doi.org/10.3905/jai.2018.20.3.079

Redhead, K. (2011). Behavioral perspectives on client mistrust of financial services. *Journal of Financial Service Professionals*, *65*(6), 50–61.

Rogers, E. M. (1962). *Diffusion of innovations*. New York, NY: Free Press.

Rosenberg, E. (2018, November 29). *The 8 best robo-advisors to use in 2018. The balance*. Retrieved from https://www.thebalance.com/best-robo-advisors-4163993

Salo, A. (2017). *Robo advisor, your reliable partner? Building a trustworthy digital investment management service*. Master's thesis, University of Tampere, Tampere, Finland. Retrieved from https://tampub.uta.fi/

Servon, L. J., & Kaestner, R. (2008). Consumer financial literacy and the impact of online banking on the financial behavior of lower-income bank customers. *Journal of Consumer Affairs*, *42*(2), 271–305. https://doi.org/10.1111/j.1745-6606.2008.00108.x

Sironi, P. (2016). *FinTech innovation: From robo-advisors to goal based investing and gamification*. Chichester, West Sussex, UK: Wiley.

Son, J. S. (2012). *Factors related to choosing between the Internet and a financial planner*. Unpublished doctoral dissertation, The Ohio State University, Columbus, Ohio. Retrieved from https://etd.ohiolink.edu/

Suoranta, M., & Mattila, M. (2004). Mobile banking and consumer behaviour: New insights into the diffusion pattern. *Journal of Financial Services Marketing*, *8*(4), 354–366. https://doi.org/10.1057/palgrave.fsm.4770132

Szmigin, I., & Foxall, G. (1998). Three forms of innovation resistance: The case of retail payment methods. *Technovation*, *18*(6–7), 459–468. https://doi.org/10.1016/S0166-4972(98)00030-3

van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, *101*(2), 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006

Xiao, J. J., Chen, C., & Chen, F. (2014). Consumer financial capability and financial satisfaction. *Social Indicators Research*, *118*(1), 415–432. https://doi.org/10.1007/s11205-013-0414-8

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