RIETI Discussion Paper Series 25-E-050

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The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 25-E-050

May 2025

The Diffusion of Robo-advisors and Changes in User Characteristics*

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Abstract

This paper analyzes the evolution of adoption and rejection patterns of robo-advisor services in Japan using panel survey data collected by the Japan Securities Dealers Association from 2017 to 2023, following the initial market introduction of these services. The empirical results show that demographic and socioeconomic characteristics—such as age, residential location, personality traits, and income—associated with adopters and active rejecters changed significantly over time. In contrast, individuals with high financial literacy exhibited stable adoption or rejection behavior, unaffected by time trends. These findings are consistent with the predictions of Rogers' diffusion of innovations theory and contribute to the literature by offering new insights into the determinants of robo-advisor usage.

JEL classifications: G23, G50, G53
Keywords: Robo-advisor, Diffusion of innovation, Fintech, Personal finance, Financial literacy

* This study is part of the project "Entrepreneurship in high-tech and high-growth start-ups" conducted at the Research Institute of Economy, Trade and Industry (RIETI). The authors are grateful for helpful comments and suggestions by Yuji Honjo, Sadao Nagaoka, Eiichi Tomiura, Kazuo Yamada, and other participants of the RIETI Discussion Paper Seminar for the paper. We are grateful to the seminar participants for their valuable comments and suggestions. We gratefully acknowledge financial support from the Japan Society for the Promotion of Science (JSPS) KAKENHI (Grant numbers: 23K20612 and 24K00286).

1. Introduction

Robo-advisors assist investors with asset allocation, risk management, rebalancing, tax optimization and more, all at a low cost. They also reduce information costs for individual investors and correct users' behavioral biases and biased beliefs (Capponi et al., 2022; D'Acunto et al., 2019; D'Acunto et al., 2022). Robo-advisors have developed rapidly and have drawn the attention of both academia and industry with regard to the characteristics of investors who use them. Previous studies have reported varying demographic characteristics of users, and no consistent findings have been obtained. While some previous studies suggest that the use of robo-advisors is unrelated to users' demographic characteristics (e.g., D'Acunto et al., 2019), others argue that personal characteristics influence the use of robo-advisors (e.g., age: Fan and Chatterjee, 2020; financial literacy: Aman, 2022; Piehlmaier, 2022; educational attainment: Isaia and Oggero, 2022; gender: Isaia and Oggero, 2022; personality: Flavia'n et al., 2022; Oehler et al., 2022).

The diffusion of a new technology such as robo-advisors is likely to have a significant effect on the characteristics of users. However, many studies have used survey data from a single point in time, and changes in the characteristics of users over time have not been fully verified using data from multiple points in time. Even if it is apparent based on data from a certain point in time that many users share a particular characteristic, it is unclear whether this is a temporary phenomenon or whether it changes over time. For example, robo-advisors tend to be used by younger people, but it is unclear whether their use will spread over time among younger people or among older people. By using data from multiple points in time, it becomes possible to observe changes in user demographics and clarify the reasons for these changes. This approach is expected to lead to a more comprehensive understanding of the factors that determine the use of robo-advisors. With the exception of Maggio and Yao (2021), who focused on fintech lending, there has been insufficient research on the spread of fintech. The aim of this paper is to use time-series survey data to examine how the characteristics of investors change as robo-advisors become more widespread.

The diffusion of innovations (DOI) theory (Rogers, 2003) explains the process by which innovations spread.[1] According to the DOI theory, the speed of adoption varies across individuals. To

[1] Another well-known framework for explaining the factors that influence users' acceptance of new technologies or systems is the technology acceptance model (TAM). Davis (1989) and Davis et al. (1989) proposed that perceived usefulness and perceived ease of use affect users' attitudes toward the use of technology, which in turn influences their behavioral intentions and ultimately leads to actual usage. Several extensions of the TAM have been developed. For example, the TAM2 by Venkatesh and Davis (2000) incorporates social influence and cognitive instrumental processes. Venkatesh et al. (2003) subsequently proposed the unified theory of acceptance and use of technology (UTAUT), which incorporates four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. These factors influence behavioral intention and usage behavior. However, in

adopt an innovation, individuals must first acquire, understand, and evaluate information and knowledge about the innovation before making a decision to adopt it. Therefore, factors such as access to information as well as individuals' level of understanding, interest, personality, and available resources can influence the time needed to reach an adoption decision. As a result, it is expected that the characteristics of users of innovations will change over time. Furthermore, over time, it is possible to understand the characteristics of people who choose not to use an innovation once they fully understand it. Rogers distinguishes between active rejection, which implies that individuals choose not to adopt an innovation despite fully understanding it, and passive rejection, which suggests that rejection occurs due to a lack of sufficient understanding. It is expected that the type of rejection will change over time.

The first asset management robo-advisor for individual investors in Japan was launched by WealthNavi in July 2016. As of the end of September 2024, there were six robo-advisor services providing asset management for individual investors in Japan. All of the asset management robo-advisors for individual investors in Japan are discretionary long-term passive investment advisors that make investment decisions automatically.[2] According to a survey by the Japan Investment Advisers Association, as of September 2024, the total market size of robo-advisors was 1.88 trillion yen with 773,900 contracts, and WealthNavi's market share was 66.7%.

For the analysis, this study utilizes a survey conducted by the Japan Securities Dealers Association (JSDA) for individual investors. The JSDA is a private self-regulatory organization equivalent to the Financial Industry Regulatory Authority (FINRA) in the United States. In Japan, entities that are engaged in securities brokerage services are required to register with and be certified by the JSDA. This survey is conducted every year with approximately 5,000 individual investors and asks about the use of robo-advisors from 2017 to 2023, the year after the introduction of robo-advisors in Japan in 2016. Therefore, it provides an appropriate means of empirically examining how the characteristics of users of robo-advisors changed from the time this technology was introduced to the present.

The main findings of this study are as follows. Characteristics such as age, personality (e.g., time discounting, risk aversion), income and place of residence have a significant relationship with the

contrast to Rogers (2003), these models do not clearly describe the effect of time on the diffusion of new technology. Therefore, we use Rogers' model to examine the impact of robo-advisor diffusion on the decision to use robo-advisors.

[2] Robo-advisors for asset management can be divided into two types: those that support short-term active trading, in which the customer is heavily involved in implementing the strategy, and those that focus on long-term passive investment, in which the robo-advisor makes most of the investment decisions (D'Acunto and Rossi 2021).

adoption or active rejection of robo-advisors, but these impacts change over time as the relationship weakens or disappears. These results are consistent with those of Rogers (2003), who argues that the rate of adoption of innovations is influenced by perceived attributes such as relative advantage, compatibility, complexity, trialability, and observability as well as by individual innovativeness. Furthermore, financial literacy and the characteristics of investment style have a consistent and significant positive effect on the use of robo-advisors over time. Financial literacy and investment style may constitute the perceptual conditions necessary for the effective use of robo-advisors, which cannot be overcome in the short term.

This study provides several contributions. First, it advances research on the characteristics of users of robo-advisors. Previous research has not produced consistent results regarding the characteristics of investors who use robo-advisors. This study suggests that some characteristics of users change with the spread of the technology, while other characteristics do not change easily. This finding provides insight into how to promote the spread of fintech and securities investment. Second, this research contributes to the study of the diffusion of innovation. In the fields of economics and business administration, many studies have examined the factors that contribute to the diffusion of innovation. This research provides additional results by examining the factors that contribute to the use or active rejection of robo-advisors over time.

The remainder of this paper is organized as follows. Section 2 describes the data and descriptive statistics. Section 3 reports and discusses the results of multivariate analysis. Section 4 presents the conclusions of this paper.

2. Data and Descriptive Statistics

2.1. Data

This paper uses data from the JSDA's "Survey on Individual Investors' Attitudes toward Securities Investment", which is an annual online survey of approximately 5,000 people aged 20 and over who hold securities in Japan. The respondents of the survey are all individuals with experience in securities investment. Since robo-advisors are also considered a form of securities investment, surveying individuals without such experience would make it difficult to distinguish between the use of robo-advisors and the use of securities investments more broadly. By limiting the sample to those with securities investment experience, this study eliminates the confounding effect of general securities investment use and isolates the issue of the use of robo-advisors for focused analysis. A question about the use of robo-advisors has been asked since July 2017, one year after the launch of robo-advisors in Japan. This study uses 35,073 samples from 2017 to 2023 to verify the results. Participants were asked the question, "Do you currently use robo-advisors or would you like to use them in the future?" with four response options: (1) currently using, (2) would like to use, (3) do not want to use, and (4) not sure. On average, across all survey periods, 3.7% of respondents answered that they were already using robo-advisors.

On the basis of the survey, two types of dependent variables are created. The first variable is *Utilization*, which is used to examine the factors that influence the use of robo-advisors. *Utilization* is a binary variable that indicates whether the respondent is currently using robo-advisors (1 = currently using, 0 = not using). We use this variable to analyze the characteristics of robo-advisor adopters. The second dependent variable is *Active rejection*, which is a binary variable created for respondents who are not currently using robo-advisors to indicate whether they explicitly do not want to use robo-advisors in the future (1 = do not want to use, 0 = otherwise). This variable serves as a proxy for active rejection. According to Rogers (2003), there are two types of rejection in the innovation decision process: active rejection and passive rejection. Active rejection occurs when an individual considers adopting an innovation but ultimately decides not to adopt it. In contrast, passive rejection occurs when an individual decides not to adopt an innovation without seriously considering its use.

The explanatory variables are defined as follows. The Age variable is classified into 11 categories in 5-year intervals, ranging from 20 years old to 70 years and above. The Sex variable is a binary variable that takes a value of 1 for male respondents and 0 for female respondents. The Time discounting variable captures the degree of present bias and is constructed on the basis of responses to the following question: "On the assumption that you will definitely receive the money, if you have two options, (1) receive 100,000 yen now or (2) receive 110,000 yen in one year, would you choose option (1)?" This response is a binary variable: “agree” is given a value of 1, while “neither agree nor disagree” or “disagree” is given a value of 0. The Risk aversion variable reflects an individual’s aversion to risk and is defined as a binary variable based on the response to the following statement: “If you invest 100,000 yen, there is a 50/50 chance of either gaining 20,000 yen or losing 10,000 yen. Would you choose not to invest?" Respondents who answer "agree" are coded as 1, indicating risk aversion, whereas those who respond "neither agree nor disagree" or "disagree" are coded as 0. The Literacy variable represents the level of financial literacy and is constructed on the basis of five survey questions. The first three questions assess knowledge of fundamental financial concepts: "Investments with above-average returns come with above-average risks" (Risk and return), "Buying the stock of a single company is generally a safer investment than buying a stock mutual fund (a financial product that invests in multiple stocks)" (Diversification in investment), and "When interest rates rise, bond prices usually fall" (Bond price). In addition, two questions about offsetting profit and loss and the defined contribution plan are used to assess knowledge of specific financial systems. Because there is bias in the correct answer rate for these questions, they are standardized for each question and the average value is calculated. The average value is therefore 0. The Tokyo variable is a binary indicator that takes a value of 1 if the respondent resides in Tokyo and 0 otherwise. The Mutual fund variable is also a binary indicator that is coded as 1 if the respondent holds mutual funds and 0 otherwise. The Income variable represents individual annual income and is categorized into eight groups: 1 = less than 3 million yen, 2 = 3 million to less than 5 million yen, 3 = 5 million to less than 7 million yen, 4 = 7 million to less than 10 million yen, 5 = 10 million to less than 12 million yen, 6 = 12 million to less than 15 million yen, 7 = 15 million to less than 20 million yen, and 8 = 20 million yen or more. Elapsed years is the natural logarithm of the number of years that have passed since the launch of the robo-advisor service. By using a cross-section with Elapsed years, it is possible to verify whether the impact of individual characteristics on the use of the service has changed over time.

2.2. Descriptive Statistics

Panel A of Table 1 presents the descriptive statistics for each variable. On average, approximately 3.7% of the respondents use robo-advisors, whereas approximately 40% actively refuse to use them. For the Age variable, the mean is 7.88 and the median is 8.00, indicating that older individuals are more prevalent in the sample. For the Sex variable, 62% of the respondents are male, suggesting that men are overrepresented in the sample. The mean values of the Time discounting and Risk aversion variables indicate that while a certain proportion of respondents exhibit these tendencies, the majority do not. The Literacy variable has a standard deviation of 0.58, which is relatively large compared with its mean, suggesting substantial variation in financial literacy among respondents. With respect to the Tokyo variable, the proportion of respondents who reside in Tokyo is slightly greater than the actual population ratio of approximately 11%; however, this difference is not considered substantial. The Mutual fund variable is an indicator of mutual fund ownership. Its mean exceeds 0.5, indicating that a relatively large proportion of respondents have access to financial products. With respect to the Income variable, the mean is approximately 2.21, which is generally consistent with the average annual income in Japan. In the test for differences in average values, people who are younger, are male, have a high level of financial literacy, live in Tokyo, own mutual funds, and have high income are more likely to use robo-advisors.

Panel B of Table 1 presents the trends in the average values of each variable from 2017 to 2023 and shows that there are no significant changes in the distribution of the variables over time. For example, the Age variable fluctuates between approximately 7.65 and 8.21, whereas the proportion of respondents who reside in Tokyo ranges from 15% to 17%, suggesting that both variables remain relatively stable. The Time discounting, Risk aversion and Literacy variables also show only slight fluctuations from year to year and are stable overall. The Mutual fund variable shows a slight increase, but the range of change is limited. The Income variable also shows only small fluctuations from year to year with no significant changes in distribution overall. Therefore, this sample is appropriate for the analysis of changes in users' characteristics because the distributions of each variable are stable over time and no specific variables show significant changes.

Table 1 Panel A

Table 1 Panel B

2.3. Trends in the Share of Robo-Advisor Users and Rejecters

Figure 1 shows the trend in the percentage of people who are using robo-advisors (*Utilization*). According to Figure 1, the proportion of individuals who use robo-advisors has gradually increased over time. In 2017, the usage rate was as low as approximately 1.1%. Although there was a slight decline in 2023, the proportion of robo-advisor users had increased to approximately 4.9% by 2022.

Figure 2 shows the trend in the proportion of respondents who do not use robo-advisors and indicate that they do not intend to use it in the future (*Active rejection*). The figure shows that the proportion of individuals who reject the use of robo-advisors has remained within a relatively stable range, around 40%, between 2018 and 2023. This finding suggests that although the overall rate of adoption of robo-advisors is increasing, a number of people continue to avoid using them.

Figure 1

Figure 2

3. Examination

3.1. Changes in User Characteristics Over Time: Heatmap Insights

Figure 3 presents a heatmap that visualizes the percentage of robo-advisor users in each age group for each year to provide a clear understanding of usage trends over time. The percentages indicate the proportion of robo-advisor users in each age group, not the share of each age group among all robo-advisor users. For example, in 2017, the robo-advisor usage rate for respondents in their 20s was 13.2%. This means that 13.2% of people in their 20s used robo-advisors that year, not that 13.2% of all robo-advisor users were in their 20s.

In 2017, immediately after robo-advisors were introduced, the usage rate was highest among people in their 20s, and this trend continued until 2020. After reaching its peak in 2020, the usage rate among this age group began to decline from 2021 onward. In fact, people in their 20s were the only age group that experienced a negative change in their usage rate between 2017 and 2023. The usage rate for people in their 30s gradually increased beginning in 2017, peaked in 2020, and has shown a declining trend since then. For people in their 40s, the initial usage rate was low but increased gradually over time. This group reached its peak in 2022, slightly later than the peaks observed for people in their 20s and 30s, with a subsequent downward trend. For people in their 50s and 60s, the initial robo-advisor usage rates were significantly lower than those in the other age groups. However, in recent years, a gradual upward trend has been observed for these age groups. The rate of change from 2017 to 2023 was also notably higher for these age groups than for the other age groups. As of 2023, the usage rate was highest among people in their 40s, followed by those in their 30s and 50s, whereas the rates for people in their 20s and 60s were nearly identical. These trends suggest that while robo-advisor usage was initially driven primarily by people in their 20s, it gradually expanded to people in their 30s and 40s. More recently, usage has begun to spread among people in their 50s and 60s.

Figure 3

Figure 4 presents a heatmap that visualizes the percentage of robo-advisor users in each income group for each year, which provides a clear understanding of usage trends over time. The percentages indicate the proportion of robo-advisor users in each income group, not the share of each income group among all robo-advisor users. For example, the robo-advisor usage rate for the income group of less than 3 million yen in 2017 was 0.6%, meaning that 0.6% of people in this income group used robo-advisors that year, not that 0.6% of all robo-advisor users were in this income group.

In 2017, soon after robo-advisors were introduced, the highest-income group (20 million yen or more) had the highest usage rate. Their usage continued to increase until 2019 but began to decline from 2020 onward. In fact, this is the only group to show a negative rate of change between 2017 and 2023. The high-income groups (between 12 million and 15 million yen and between 15 million and 20 million yen) also had relatively high initial usage rates and have shown an upward trend since 2017. Following the highest-income group, these high-income groups reached their peak in 2020 but have shown a declining trend since 2021. The middle-income groups (between 5 million and 7 million yen, 7 million and 10 million yen, and 10 million and 12 million yen) showed low initial usage rates in 2017 that have increased steadily over time. These groups likely reached their peak between 2021 and 2023. The change rate from 2017 to 2023 is also noticeably higher for these middle-income groups than for the other groups. The low-income groups (those with income less than 3 million yen and those with income between 3 million and 5 million yen) had very low usage rates in the early stages. However, their usage has gradually increased, and further growth is expected. These trends suggest that the use of robo-advisors was initially driven by high-income groups, expanded to middle-income groups, and is now gradually gaining traction among low-income groups.

Figure 4

3.2. Changes in User Characteristics Over Time

Table 2 shows the percentage of robo-advisor users with financial literacy levels above and below the median for the entire survey period (Total) and over time. It also indicates whether the difference between the two groups is statistically significant. The comparison over the entire survey period (Total) reveals a statistically significant difference between the two groups, suggesting that higher levels of financial literacy may have a substantial effect on robo-advisor usage. The time series analysis also confirms a significant difference every year. Although the difference was slightly smaller in the initial year, 2017, the significance remained consistently strong in the following years. This finding indicates that regardless of the period, higher levels of financial literacy are an important determinant of robo-advisor usage.

For each of the five questions (Diversification in investment, Risk and return, Bond price, Offsetting profit and loss, and Defined contribution plan) used to construct Literacy variable, the table presents the percentage of robo-advisor users among those who answered correctly or were knowledgeable and those who answered incorrectly or did not know for both the entire survey period (Total) and over time. The comparison over the entire survey period (Total) shows that there are highly significant differences for all items. The time series analysis further reveals that knowledge of offsetting profit and loss and the defined contribution plan consistently shows strong significance across all years. More specialized financial knowledge, especially in these areas, may therefore have a substantial effect on robo-advisor usage.

Table 2

Table 3 presents the percentage of robo-advisor users for each of the variables, Sex, Time discounting, Risk aversion, and Living place (Tokyo), for the entire survey period (Total) and over time. It also shows whether the differences between groups are statistically significant. For sex, this table compares the percentage of male and female users of robo-advisors and indicates whether the difference is significant. The results show that over the entire survey period, the percentage of male robo-advisor users was significantly greater than the percentage of female users. In the time series analysis, no significant difference was observed in the initial year, 2017. However, from 2018 onward, despite some fluctuations, a similar trend persisted. These findings suggest that men have consistently been more active in using robo-advisors.

Time discounting indicates the percentage of robo-advisor users who are more present-biased and those who are not for the entire survey period (Total) and over time. It also indicates whether the difference between the two groups is statistically significant. No significant difference was found between the two groups over the entire survey period (Total). In the time series analysis, in 2017, the percentage of robo-advisor users among respondents with a present bias was greater with a significant difference. Subsequently, the percentage of both groups fluctuated from year to year, but no significant difference was confirmed. This finding suggests that in the early stages, present bias was a determining factor in the adoption of robo-advisors but gradually weakened.

With regard to risk aversion, the percentage of risk-averse individuals who use robo-advisors is shown for all survey years (Total) and over time, as is the percentage of non-risk-averse individuals who use robo-advisors and whether there is a significant difference between the two. For all survey years (Total), no significant difference was found between the two groups. In the time series analysis, as with time discounting, the percentage of risk-averse people who used robo-advisors was greater in 2017, and a significant difference was confirmed. Subsequently, the percentage of both groups fluctuated from year to year, but no significant difference was confirmed. However, in 2023, a larger percentage of non-risk-averse people used robo-advisors, and a significant difference was confirmed. While being risk averse was a determining factor in the initial adoption of robo-advisors, it gradually became less of a determining factor.

With regard to residence, the percentage of robo-advisor users among people living in Tokyo is shown for all survey years (Total) and over time, as is the percentage of robo-advisor users among those living outside Tokyo. Statistical significance was tested between the two groups. For all survey years (Total), the percentage of robo-advisor users among people who lived in Tokyo was significantly greater than the percentage among people who did not live in Tokyo. In the time series analysis, the percentage of robo-advisor users among people who lived in Tokyo was greater in 2017, with a significant difference. Although no significant difference was found subsequently, the difference in the proportion of the two gradually narrowed such that the proportion of robo-advisor users who do not live in Tokyo is higher. Therefore, while living in Tokyo was a deciding factor in the introduction of robo-advisers in the early stages, it gradually became less of a deciding factor.

Table 3

3.3. Regression Results and Theoretical Considerations

On the basis of the heatmap analysis and t tests described above, we examined the simple relationships between the acceptance or rejection of robo-advisers and each variable. However, these methods make it difficult to capture the simultaneous effects of multiple factors. Therefore, we also conducted a logistic regression analysis on the acceptance or rejection of robo-advisors. In addition, we attempted a theoretical interpretation of the analysis results from the perspective of Rogers' diffusion of innovations (DOI) theory, a representative theory of technology acceptance. This study aims to demonstrate how robo-advisers spread throughout society over time. The DOI explains how innovations diffuse over time.[3]

3.3.1. Theoretical Framework

To provide a theoretical interpretation of the regression results, we first offer an overview of the DOI theory. The definition presented below is based on Rogers (2003).[4,5] The DOI theory, proposed by Rogers (2003), is a theory that explains how innovations spread over time. According to the theory, individuals go through five stages when deciding whether to adopt an innovation: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003, pp. 168–194). First, in the knowledge stage, individuals become aware of the existence of an innovation and begin to understand how it functions. Next, in the persuasion stage, they form a favorable or unfavorable attitude toward the innovation. This stage is particularly important in the adoption process because it is influenced by five perceived attributes: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003, pp. 219–265). Relative advantage refers to the degree to which an innovation is perceived as better than the existing alternatives. Compatibility is the degree to which the innovation is perceived as consistent with existing values, past experiences, and the needs of potential adopters. Complexity refers to the degree to which the innovation is perceived as relatively difficult to understand and use. Trialability is the extent to which an innovation can be tried. Observability refers to the degree to which the results of the innovation are visible to others. In the decision stage, individuals choose whether to adopt or reject the innovation. Rogers (2003) distinguishes between two

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[3] The TAM and the UTAUT focus primarily on explaining individual technology acceptance from the perspectives of cognition and intention. However, they do not provide a detailed account of how technologies diffuse over time, which is the central focus of our study and is an aspect more thoroughly addressed by DOI.

[4] The TAM was proposed by Davis (1989) and Davis et al. (1989). In the TAM, two key factors—perceived usefulness and perceived ease of use—affect an individual's intention to use technology. According to Davis (1989) and Davis et al. (1989), perceived usefulness refers to the degree to which a person believes that using a particular technology will enhance his or her job performance, while perceived ease of use refers to the degree to which a person believes that using the technology will be free of effort.

Venkatesh and Davis (2000) proposed the TAM2 as an extension of the original technology acceptance model. The TAM2 explains perceived usefulness and the behavioral intention to use technology by incorporating two sets of determinants: social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use).

[5] The unified theory of acceptance and use of technology (UTAUT) was proposed by Venkatesh et al. (2003). The UTAUT integrates eight existing models of technology acceptance. It identifies four key factors that influence the behavioral intention to use technology and actual usage: performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, four moderating variables—gender, age, experience, and voluntariness of use—affect the relationships between these factors and both intention and behavior.

types of rejection: active rejection, in which the individual makes an informed decision not to adopt the innovation, and passive rejection, in which the innovation is rejected owing to a lack of sufficient understanding (pp. 177–178). To make a decision about adoption or rejection, individuals must first understand and perceive the innovation. Since the time required for this process varies from person to person, the rate at which individuals adopt or reject innovations also differs.[6]

3.3.2. Regression Results and Theoretical Considerations

Table 4 and Table 5 show the results of logistic regression analysis of the marginal effects with the use of robo-advisors as the dependent variable. Table 4 shows the results of verifying the factors that determine whether to use robo-advisors using the entire sample. Table 5 shows the results of verifying the factors that determine active rejection, i.e., the decision not to use robo-advisors in the future, among respondents who do not use robo-advisors. Model 2 in both tables incorporates cross terms between the natural logarithm of the number of years since the launch of the robo-advisor service (Elapsed years) and variables related to personal characteristics. The cross terms indicate how the influence of personal characteristics on service usage changes over time. If the coefficients of the cross terms are significant, the influence of that variable changes over time. For example, if the coefficient of a single variable is positive and the coefficient of the cross term with Elapsed years is negative, it indicates that the variable had a positive effect on the introduction in the initial stage, but its effect gradually weakened over time.

As shown in Table 4, the coefficients for the individual Age term in Models 1 and 2 are negative and statistically significant. This finding is consistent with previous research (Nicholson et al., 2005; Okun, 1976; Prenski, 2001; Wood, 2002) that suggests that (1) younger individuals tend to have greater affinity for and interest in new technologies and face lower barriers to understanding and usage, and/or (2) older individuals are less likely to use robo-advisors owing to the higher psychological costs associated with adopting new technologies, such as the need to unlearn existing rules.

In contrast, the coefficient of the cross term of Age and Elapsed years in Model 2 is positive and significant. This finding indicates that the increase in robo-advisor usage over time is not due to its spread among younger individuals but rather to its growing adoption among older age groups. These results suggest that although older individuals may have more difficulty than younger individuals in perceiving the complexity and relative advantage of adopting robo-advisors, their perceptions may deepen over time, leading to an increase in usage.[7]

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[6] Rogers (2003) refers to the earliest adopters as innovators and describes them as adventurous, daring, and willing to take risks. They possess the ability to cope with uncertainty and risk as well as the technical knowledge necessary to understand new innovations (pp. 282–283).

[7] The same applies to perceived usefulness and perceived ease of use in the TAM as well as to performance expectancy and effort expectancy in the UTAUT. In particular, the UTAUT posits that

In Models 1 and 2 of Table 5, the coefficient for the individual Age term is positive and significant, and in Model 2, the coefficient of the cross term of Age and Elapsed years is negative and significant. These results suggest that over time, either older individuals are becoming less likely to reject robo-advisors or younger individuals are becoming more likely to do so. It is possible that older individuals became less likely to reject robo-advisors over time as they came to perceive their usefulness and/or that younger individuals became more likely to reject robo-advisors after realizing that they did not meet their initial expectations.

In Table 4, the coefficients for the individual Time discounting term in Models 1 and 2 are positive and statistically significant. Compared with traditional financial services, robo-advisors can be accessed through simpler procedures and lower costs. This result may be interpreted as indicating that individuals with a strong present bias are more likely to use robo-advisors because they perceive them as offering greater usefulness through immediate benefits.[8] This finding is consistent with the findings of previous studies (O'Donoghue and Rabin, 1999).

In contrast, the coefficient for the interaction term between Time discounting and Elapsed years in Model 2 is negative and statistically significant. This suggests that rather than robo-advisors spreading among individuals with a strong present bias, their increased usage over time is driven by people with a lower degree of present bias. These results suggest that individuals with a lower amount of present bias may take more time to decide to adopt robo-advisors than people with a greater present bias because the former group is less biased and therefore takes longer to perceive the usefulness of this technology. This delay in perception may explain the gradual increase in users over time.

In Model 2 of Table 5, the interaction term between Time discounting and Elapsed years is positive and statistically significant. This finding indicates that the rejection of robo-advisors decreases over time among people with low present bias. This may be because people with significantly low present bias tend to act very cautiously, which leads them to reject the early adoption of robo-advisors; however, over time, their understanding of the usefulness of robo-advisors deepens, causing them to change their rejection.

In Table 4, Models 1 and 2, the coefficient of the Risk aversion variable is positive and statistically significant. This finding suggests that risk-averse individuals are likely to adopt robo-advisors at an early stage. This may not be consistent with Rogers' (2003) idea that risk-seeking individuals are more likely to actively adopt new technologies. Robo-advisors are designed on the basis of portfolio theory, which diversifies risk, and are therefore perceived as highly useful for risk-averse individuals, which may have encouraged their use among this group.

In Model 2, the interaction term between Risk aversion and Elapsed years is negative and

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the effects of performance expectancy and effort expectancy on behavioral intention are moderated by age.

[8] There are various interpretations of time discounting. For example, see Frederick et al. (2002).

statistically significant. This suggests that rather than robo-advisors becoming more widely adopted among risk-averse individuals over time, their usage among risk-seeking individuals has increased. Given the inherently risk-averse nature of robo-advisors, this result implies that risk-seeking individuals may initially find it more difficult than risk-averse individuals to perceive the relative advantages of robo-advisors. However, as they observe performance outcomes and gain more information over time, their perceptions of robo-advisors' usefulness may deepen, leading to a gradual increase in adoption.

In Table 5, the coefficient of the Risk aversion variable is positive and statistically significant, whereas the interaction term is not statistically significant. This may indicate that a certain portion of risk-averse individuals do not necessarily evaluate robo-advisors positively because of reduced investment risk but rather tend to reject the adoption of new technologies such as robo-advisors. Moreover, this tendency may not diminish even approximately seven years after the introduction of the technology. These findings are consistent with the perspective of Rogers (2003).

In Table 4, Models 1 and 2, the coefficient for the Literacy variable is positive and statistically significant. Because robo-advisors are designed on the basis of financial theory, it is possible that a certain level of financial knowledge is required to fully understand their usefulness. This result is consistent with those of previous studies (Aman, 2022; Piehlmaier, 2022). In addition, the interaction term between literacy and elapsed years is not statistically significant. This suggests that even as time passes, individuals with low financial literacy remain reluctant to adopt robo-advisors. Given the nature of robo-advisors, this result implies that a period of seven years may not be sufficient for individuals with low financial literacy to fully perceive their usefulness.

Table 5 shows that in both Models 1 and 2, the coefficient for Literacy is positive and significant, whereas the interaction with Elapsed years does not reach statistical significance. Among individuals with high financial literacy, some may have already established their own investment styles and asset management strategies. Compared with robo-advisors, these individuals may perceive their own approach as having greater relative advantages and may determine early on that robo-advisors are less compatible with their existing practices. As a result, they may consistently decide to reject robo-advisors from an early stage.

In Table 4, Model 2, the coefficient for the Tokyo variable is positive and statistically significant. Tokyo is the center of Japan's stock market and has easy access to information on robo-advisor services, which may make it an attractive environment for adoption. However, the interaction term between Tokyo and Elapsed years is negative and statistically significant. These findings suggest that over time, the adoption of robo-advisors has increased among individuals residing outside Tokyo. Although non-Tokyo residents may initially face greater difficulty in perceiving the observability of robo-advisors compared to people in Tokyo, the gradual reduction in regional disparities over time may increase their perception and contribute to increased adoption rates. This interpretation aligns with Rogers'

(2003) view, which posits that access to information facilitates perception and ultimately leads to adoption decisions.

In Table 4, Models 1 and 2, the coefficient for the Mutual fund variable is positive and statistically significant. Mutual fund investors typically have a sound understanding of investment risk and financial product management. Given that robo-advisors also offer risk diversification through portfolio mechanisms similar to mutual funds, it is plausible that mutual fund holders possess the financial literacy required to recognize robo-advisors' usefulness, potentially leading to higher adoption rates. In contrast, the interaction term between Mutual and Elapsed years in Model 2 is not statistically significant. This suggests that individuals who hold mutual funds continue to adopt robo-advisors over time. This finding implies that mutual fund holders are more likely to perceive robo-advisors' relative advantage and compatibility. Given the nature of robo-advisors, this effect, which is similar to that of financial literacy, may not decrease significantly even over a period of seven years.

In Table 5, Model 2, the coefficient for the Mutual fund variable is negative and statistically significant, whereas the interaction term between Mutual fund and Elapsed years is positive and statistically significant. This finding suggests that over time, the rejection of robo-advisors among individuals who do not hold mutual funds has decreased. This result may indicate that increased observability of robo-advisors has gradually lowered the barriers to adoption, even for those without mutual fund holdings.

In Table 4, Model 1, the coefficient for Income is positive and statistically significant. Because high-income individuals can mitigate the impact of potential losses, they tend to face fewer barriers to risk-taking. This observation is consistent with prior research (Weber and Hsee, 1998; Hallahan, Faff and Mckenzie, 2004).

In contrast, in Model 2, the interaction term between Income and Elapsed years is negative and statistically significant. This suggests that rather than robo-advisors becoming more widespread among high-income individuals over time, their usage has increased among lower-income individuals. One possible interpretation is that compared with their higher-income counterparts, lower-income individuals may initially find it more difficult to perceive the trialability of robo-advisors. However, as time passes, their perceptions may gradually deepen, leading to increased adoption.

In Table 5, the coefficient for Income is negative and statistically significant in Model2, whereas the interaction term between Income and Elapsed years is positive and statistically significant. These results suggest that over time, the rejection of robo-advisors has decreased among low-income individuals or increased among high-income individuals. One possible explanation is that low-income individuals have come to perceive robo-advisors as more useful, leading to reduced rejection. Another possibility is that high-income individuals tried robo-advisors and found them different from what they expected, which may have resulted in increased rejection.

Tables 4 and 5 show that rather than increasing among people with similar characteristics over time, the use (or rejection) of robo-advisors is shifting toward people with different characteristics. People who are early users (or rejecters) of robo-advisors tend to have characteristics that make them more likely to perceive the usefulness of this technology sooner, whereas those who use (or reject) robo-advisors later tend to have characteristics that make them take longer to perceive their usefulness. These findings are generally consistent with the DOI theory (Rogers, 2003), the TAM (Davis, 1989; Davis et al., 1989), and the UTAUT (Venkatesh et al., 2003).

Table 4

Table 5

4. Conclusion

This paper empirically analyzed how the characteristics of users have changed in the context of the rapid development of robo-advisors. The analysis revealed that, in particular, age, personality, income and place of residence play important roles in the use of robo-advisors and that their influence changes from year to year. These results are consistent with Rogers' diffusion theory of innovation. On the other hand, financial literacy and investment style consistently have a significant effect on use and rejection. Robo-advisors are relatively recent technology and can be considered to be in the process of widespread adoption. Furthermore, since robo-advisors are a new market, changes such as the acquisition of start-up companies may influence the decision to adopt or reject them. This study focuses on decision-making factors at the individual level, so factors such as the impact of startup acquisitions were not considered. Addressing these elements in future research would be an important step toward a more comprehensive analysis. In the future, it is hoped that more data will be accumulated and that further research will be conducted.

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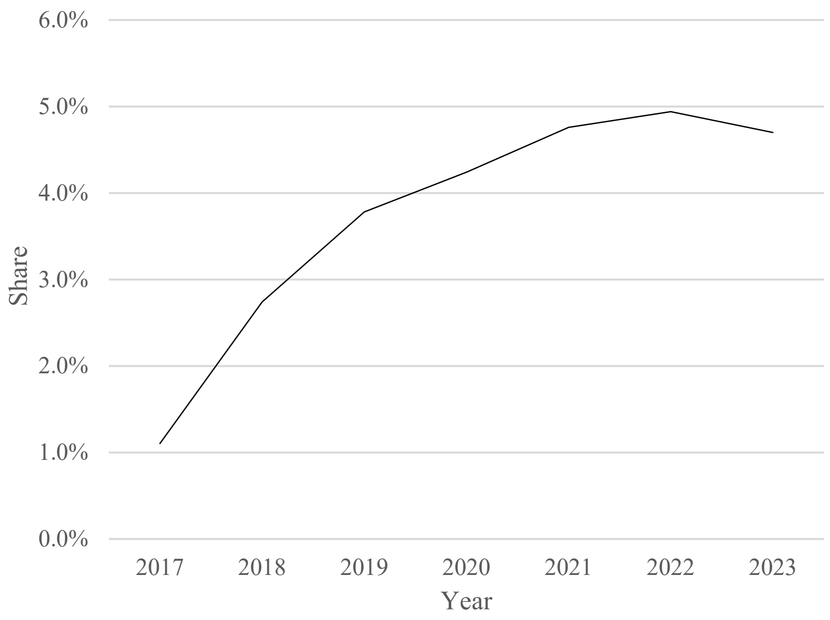

Figure 1. Trend in the Share of Robo-Advisor Users

Figure 1 shows the change in the percentage of robo-advisor users based on survey responses from 2017 to 2023. The horizontal axis shows the year, and the vertical axis shows the percentage of people who responded that they used robo-advisors. This makes it possible to clearly understand the change in the percentage of robo-advisor users over time.

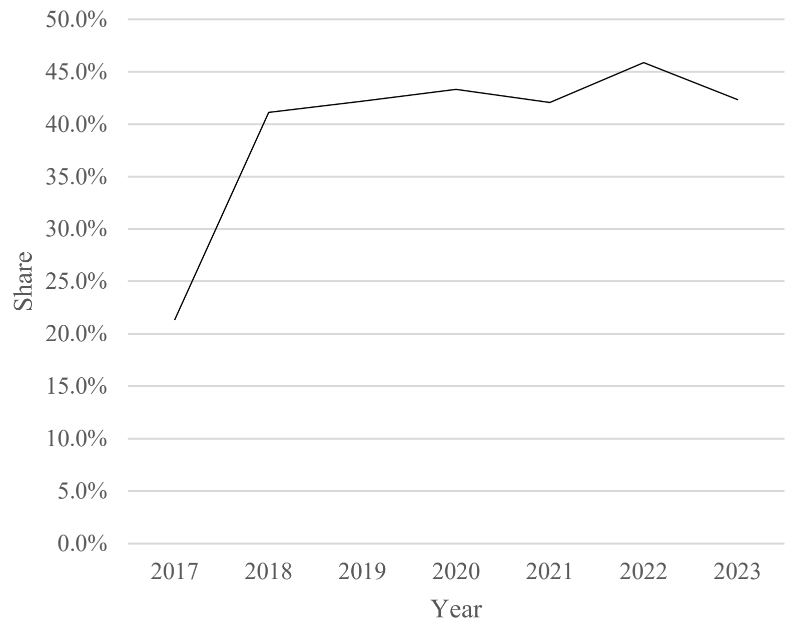

Figure 2. Trend in the Share of Robo-Advisor Rejecters

Figure 2 shows the change in the percentage of respondents who refused to use robo-advisors based on survey responses from 2017 to 2023. The horizontal axis shows the year, and the vertical axis shows the percentage of respondents who refused to use robo-advisors. This makes it possible to clearly understand the change in the percentage of robo-advisor rejecters over time.

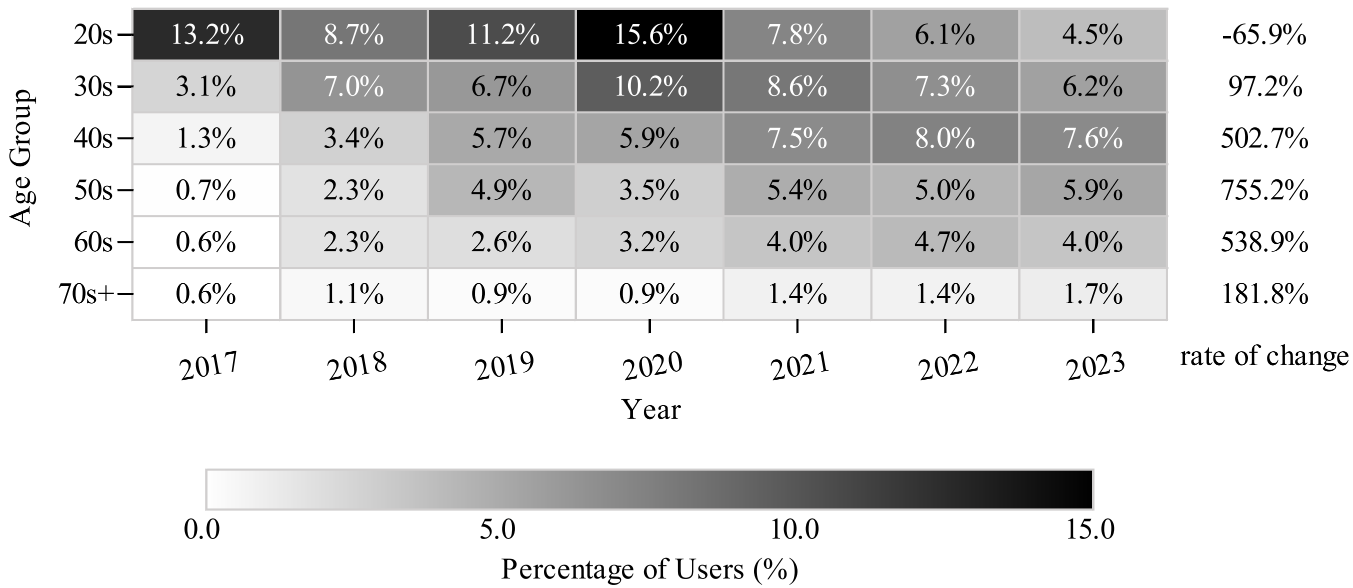

Figure 3. Heatmap of Changes in Robo-Advisor User by Age

Figure 3 shows a heatmap that visualizes the percentage of robo-advisor users in each age group for each year. This provides a visual understanding of the trends in robo-advisor usage over time. The vertical axis represents the age group, whereas the horizontal axis represents the year. The percentage values show the percentage of robo-advisor users in each age group, not the percentage of each age group in the total number of robo-advisor users. The rate of change represents the percentage change from 2017 to 2023.

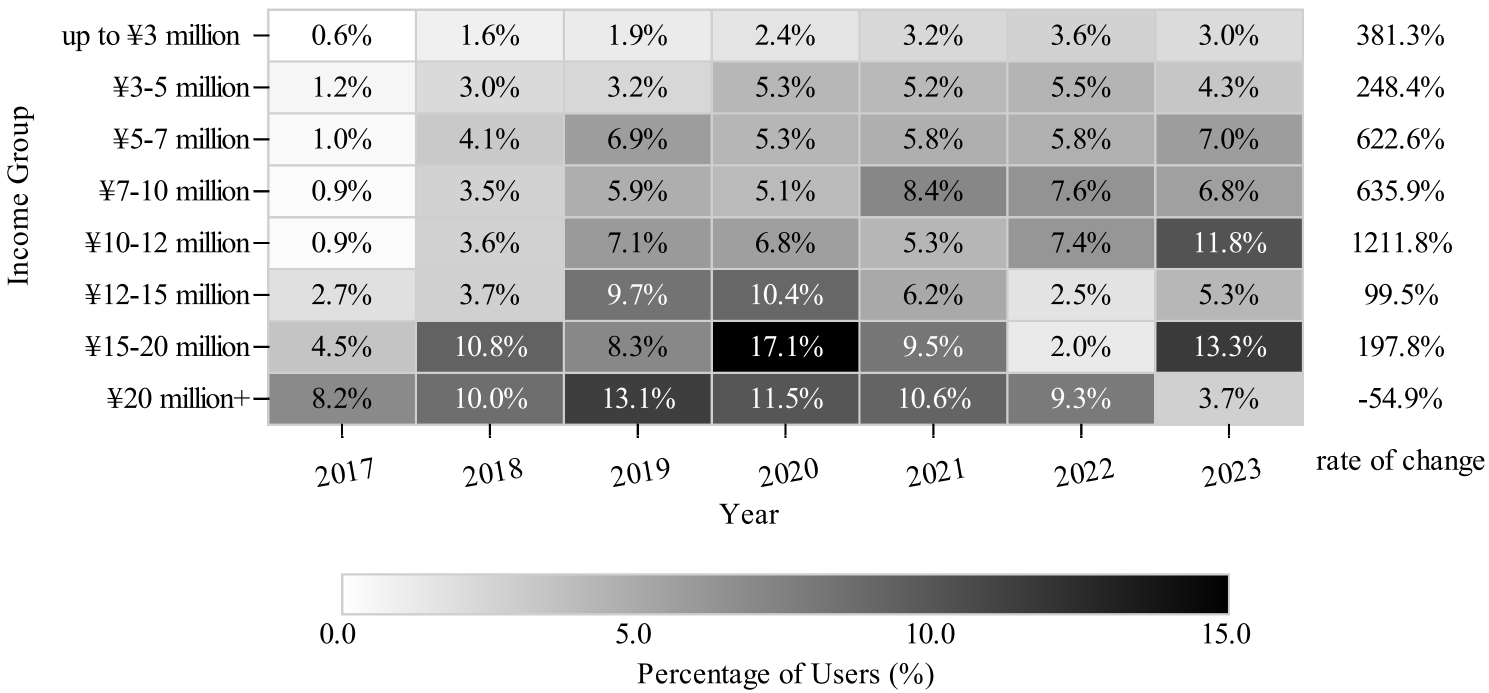

Figure 4. Heatmap of Changes in Robo-Advisor User by Income

Figure 4 presents a heatmap that visualizes the percentage of robo-advisor users in each income group for each year. This provides a visual understanding of the trends in robo-advisor usage over time. The vertical axis represents the income group, whereas the horizontal axis represents the year. The percentage values show the percentage of robo-advisor users in each income group, not the percentage of each income group in the total number of robo-advisor users. The rate of change represents the percentage change from 2017 to 2023.

Table 1. Summary statistics

Panel A. Descriptive statistics for the full sample

			Percentile					
Variable	Mean	S.D.	25th	50th	75th	Obs.	Diff	
Utilization	0.037	0.190	0.000	0.000	0.000	35,073	-	
Active rejection	0.396	0.489	0.000	0.000	1.000	33,759	-	
Age	7.882	2.727	6.000	8.000	10.000	35,073	1.604	***
Sex	0.622	0.485	0.000	1.000	1.000	35,073	-0.087	***
Time discounting	0.376	0.484	0.000	0.000	1.000	35,073	0.006	
Risk aversion	0.298	0.457	0.000	0.000	1.000	35,073	0.021	
Literacy	0.000	0.584	-0.405	-0.005	0.395	35,073	-0.229	***
Tokyo	0.167	0.373	0.000	0.000	0.000	35,073	-0.024	**
Mutual fund	0.567	0.496	0.000	1.000	1.000	35,073	-0.257	***
Income	2.205	1.469	1.000	2.000	3.000	35,073	-0.548	***

Panel B: Mean values of user demographics by year

Year	Obs.	Age	Sex	Time discounting	Risk aversion	Literacy	Tokyo	Mutual fund	Income
2017	5,073	7.648	0.790	0.383	0.299	-0.056	0.172	0.530	2.515
2018	5,000	8.210	0.590	0.402	0.297	0.009	0.166	0.522	2.158
2019	5,000	7.989	0.581	0.379	0.309	0.037	0.153	0.538	2.136
2020	5,000	7.986	0.581	0.375	0.313	0.001	0.175	0.553	2.131
2021	5,000	7.990	0.581	0.375	0.291	-0.001	0.173	0.597	2.116
2022	5,000	7.678	0.614	0.357	0.287	0.012	0.173	0.610	2.178
2023	5,000	7.676	0.614	0.360	0.287	0.000	0.157	0.617	2.197
Total	35,073	7.882	0.622	0.376	0.298	0.000	0.167	0.567	2.205

Table 2. Use of robo-advisors by financial literacy variables

Variable	Total	Year							Obs.
		2017	2018	2019	2020	2021	2022	2023	
Literacy									
Above median (a)	4.7%	1.4%	3.6%	4.4%	5.5%	5.8%	5.8%	6.1%	18,682
Below median (b)	2.7%	0.8%	1.7%	3.0%	2.8%	3.6%	3.9%	3.1%	16,391
diff (a) - (b)	2.01%	0.7%	1.9%	1.5%	2.7%	2.2%	1.9%	3.0%	
t-stat	9.88***	2.23*	4.13***	2.69**	4.78***	3.66***	3.02**	4.99***	
Diversification in investment									
Correct (a)	4.1%	0.9%	3.0%	4.3%	4.5%	5.2%	5.2%	5.1%	25,532
Incorrect (b)	2.9%	1.6%	2.1%	2.4%	3.7%	3.4%	3.8%	3.5%	9,541
diff (a) - (b)	1.2%	-0.7%	0.9%	1.9%	0.8%	1.8%	1.4%	1.6%	
t-stat	5.40***	-2.15*	1.82	3.11**	1.22	2.53*	1.90	2.35*	
Risk and return									
Correct (a)	3.8%	1.2%	2.7%	3.9%	4.4%	4.8%	4.9%	5.0%	30,586
Incorrect (b)	3.1%	0.8%	3.3%	3.1%	3.1%	4.3%	5.2%	2.8%	4,487
diff (a) - (b)	0.7%	0.3%	-0.7%	0.8%	1.2%	0.6%	-0.3%	2.1%	
t-stat	2.37*	0.89	-1.00	0.88	1.36	0.65	-0.28	2.36*	
Bond price									
Correct (a)	4.2%	1.3%	3.3%	4.0%	4.7%	5.3%	5.4%	5.2%	17,078
Incorrect (b)	3.3%	0.9%	2.2%	3.6%	3.8%	4.3%	4.5%	4.2%	17,995
diff (a) - (b)	0.8%	0.4%	1.0%	0.5%	1.0%	1.0%	0.9%	1.0%	
t-stat	4.06***	1.43	2.21*	0.86	1.68	1.60	1.39	1.75	
Offsetting profit and loss									
Known (a)	4.8%	1.6%	3.6%	4.7%	5.7%	6.0%	6.0%	6.5%	17,954
Unknown (b)	2.6%	0.6%	1.7%	2.6%	2.7%	3.6%	3.9%	3.1%	17,119
diff (a) - (b)	2.2%	1.1%	1.8%	2.1%	3.0%	2.4%	2.1%	3.4%	

t-stat	10.90***	3.69***	3.99***	3.95***	5.29***	4.00***	3.43***	5.61***	
Defined contribution plan									
Known (a)	5.5%	1.9%	4.1%	5.8%	6.7%	6.6%	6.8%	6.8%	17,928
Unknown (b)	1.9%	0.3%	1.3%	1.4%	1.9%	2.9%	3.1%	2.4%	17,145
diff (a) - (b)	3.6%	1.6%	2.8%	4.4%	4.8%	3.8%	3.7%	4.4%	
t-stat	18.05***	5.44***	6.08***	8.17***	8.56***	6.28***	6.01***	7.43***	

Table 2 shows the percentage of robo-advisor users with financial literacy levels above and below the median for the entire survey period (Total) and over time. This table also indicates whether the difference between the two groups is statistically significant. Additionally, this table shows the percentage of robo-advisor users among those who answered correctly or were aware of each of the five questions (diversification in investment, risk and return, bond price, offsetting profit and loss, and defined contribution plan) used to construct the Literacy variable as well as the proportion among those who answered incorrectly or were unaware. These results are also presented for the entire survey period and over time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Use of robo-advisors by other demographics

Variable	Total	Year							Obs.
		2017	2018	2019	2020	2021	2022	2023	
Sex									
Male (a)	4.2%	1.1%	3.3%	4.9%	4.9%	5.6%	5.5%	5.5%	21,813
Female (b)	2.9%	1.0%	2.0%	2.2%	3.4%	3.5%	4.0%	3.4%	13,260
diff (a) - (b)	1.3%	0.1%	1.3%	2.6%	1.5%	2.1%	1.5%	2.2%	
t-stat	6.37***	0.25	2.68**	4.84***	2.53*	3.45***	2.34*	3.54***	
Time discounting									
Time discount (a)	3.7%	1.6%	2.7%	3.4%	3.9%	5.0%	4.5%	5.1%	13,191
Not time discount (b)	3.8%	0.8%	2.8%	4.0%	4.4%	4.6%	5.2%	4.5%	21,882
diff (a) - (b)	-0.1%	0.8%	-0.1%	-0.7%	-0.6%	0.3%	-0.7%	0.6%	
t-stat	-0.42	2.64**	-0.19	-1.17	-0.95	0.50	-1.13	1.02	
Risk aversion									
Averse (a)	3.5%	1.6%	2.4%	3.7%	4.0%	4.9%	4.4%	3.6%	10,439
Not averse (b)	3.9%	0.9%	2.9%	3.8%	4.4%	4.7%	5.2%	5.2%	24,634
diff (a) - (b)	-0.4%	0.7%	-0.5%	-0.1%	-0.4%	0.3%	-0.8%	-1.6%	
t-stat	-1.60	2.13*	-0.90	-0.23	-0.65	0.39	-1.15	-2.42*	
Living place									
Tokyo (a)	4.3%	2.2%	3.7%	4.7%	5.0%	5.0%	4.8%	4.5%	5,863
Not Tokyo (b)	3.6%	0.9%	2.5%	3.6%	4.1%	4.7%	5.0%	4.7%	29,210
diff (a) - (b)	0.6%	1.3%	1.2%	1.1%	0.9%	0.2%	-0.1%	-0.3%	
t-stat	2.29*	3.35***	1.92	1.45	1.26	0.30	-0.14	-0.34	

Table 3 shows the percentage of robo-advisor users in each group for the following variables: Sex (female or male), Time discounting (time discounting or not), Risk aversion (risk averse or not), and Living place (Tokyo or outside Tokyo). The results are shown for the entire survey period (Total) and over time. This table also indicates whether the differences between the two groups are statistically significant. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Regression results for use of robo-advisors

Variable	Model 1		Model 2	
	dy/dx	z-stat	dy/dx	z-stat
Age	-0.006***	(-15.93)	-0.012***	(-9.90)
Sex	0.006**	(2.46)	-0.001	(-0.08)
Time discounting	0.006***	(3.03)	0.015***	(2.75)
Risk aversion	0.002	(0.85)	0.014**	(2.49)
Literacy	0.018***	(8.75)	0.018***	(3.94)
Tokyo	0.002	(0.59)	0.016***	(2.60)
Mutual fund	0.036***	(13.38)	0.045***	(6.88)
Income	0.005***	(6.77)	0.007***	(4.26)
Elapsed years	0.020***	(11.38)	0.008	(1.05)
Elapsed years x Age			0.004***	(5.50)
Elapsed years x Sex			0.005	(1.04)
Elapsed years x Time discounting			-0.006*	(-1.65)
Elapsed years x Risk aversion			-0.008**	(-2.30)
Elapsed years x Literacy			0.000	(-0.15)
Elapsed years x Tokyo			-0.010**	(-2.56)
Elapsed years x Mutual fund			-0.006	(-1.33)
Elapsed years x Income			-0.002*	(-1.76)
Pseudo R2	0.095		0.099	
Obs.	35,073		35,073	

Table 4 presents the marginal effects from logistic regression analyses, where robo-advisor usage is the dependent variable. Model 2 incorporates the natural logarithm of the number of years elapsed since the launch of the robo-advisor service (Elapsed years) into Model 1. This table shows whether the influence of individual characteristics on the use of robo-advisor changes over time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Regression results for active rejection of robo-advisors

Variable	Model 1		Model 2	
	dy/dx	z-stat	dy/dx	z-stat
Age	0.020***	(19.66)	0.035***	(13.10)
Sex	0.015***	(2.57)	-0.046***	(-3.25)
Time discounting	0.013**	(2.40)	-0.017	(-1.40)
Risk aversion	0.049***	(8.62)	0.061***	(4.88)
Literacy	0.086***	(18.64)	0.087***	(8.70)
Tokyo	0.024***	(3.42)	0.013	(0.83)
Mutual fund	-0.045***	(-8.45)	-0.082***	(-7.04)
Income	-0.002	(-1.20)	-0.011**	(-2.56)
Elapsed years	0.106***	(26.35)	0.121***	(6.45)
Elapsed years x Age			-0.011***	(-6.03)
Elapsed years x Sex			0.046***	(4.58)
Elapsed years x Time discounting			0.023***	(2.69)
Elapsed years x Risk aversion			-0.01	(-1.08)
Elapsed years x Literacy			0.000	(-0.05)
Elapsed years x Tokyo			0.009	(0.79)
Elapsed years x Mutual fund			0.028***	(3.36)
Elapsed years x Income			0.008**	(2.44)
Pseudo R2	0.034		0.036	
Obs.	33,759		33,759	

Table 5 presents the marginal effects from logistic regression analyses where robo-advisor rejection is the dependent variable. Model 2 incorporates the natural logarithm of the number of years elapsed since the launch of the robo-advisor service (Elapsed years) into Model 1. This table shows whether the influence of individual characteristics on robo-advisor rejection changes over time. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.