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Artificial intelligence in financial services: a systems dynamics approach

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Abstract

The adoption of Artificial Intelligence (AI) in the form of robo-advisors has transformed the landscape of the financial advisory industry. A system dynamics model was developed to understand better the complex, interrelated factors that drive their adoption. This model provides a simplified representation of the intricate factors that impact the adoption of robo-advisors. The subsequent steps have been detailed to report future plans. Using the data collected, a set of differential equations will be formulated and tested through a series of pre-test scenarios. The model validation, model calibration, and sensitivity analysis procedure are discussed. The aim is to refine and expand the model to yield valuable insights into adopting robo-advisors, allowing the assessment of different strategies and analysis of managerial implications. The findings of this model can assist financial service providers and investors in making informed decisions regarding the implementation of robo-advisory services.

Keywords: Artificial intelligence, Robo-advisors, Systems dynamics, Fintech

Introduction

Robo-advisors are becoming increasingly popular as more investors seek low-cost, convenient, and automated investment solutions. Robo-advisors are investment platforms that use artificial intelligence (AI) and machine learning algorithms to provide financial advice and manage portfolios for individuals (Ngo-Ye, Choi, & Cummings, 2018). The adoption of robo-advisors has been growing steadily. According to a report by Statista (2019), the total assets under management by robo-advisors globally are projected to reach $1.4 trillion by 2023. This growth can be attributed to several factors, including convenience, accessibility, and lower costs (Statista, 2019).

The use of AI in robo-advisors is revolutionizing the way people invest and manage their wealth. Robo-advisors use AI algorithms to analyze market trends and make investment decisions based on the individual's risk tolerance, investment goals, and portfolio diversification needs. The algorithms constantly monitor the market and adjust the portfolio as needed, ensuring that investments align with the individual's goals. Robo-advisors use AI to assess and manage risk in a portfolio. The algorithms consider factors such as market volatility, economic indicators, and the individual's investment goals to determine the optimal risk level for each portfolio.

By using AI to monitor risk levels, robo-advisors can minimize potential losses and maximize client returns. AI algorithms are used to segment customers into different categories based on their investment goals, risk tolerance, and financial background. This helps robo-advisors provide personalized investment recommendations and portfolio management strategies tailored to the individual's specific needs. AI algorithms use historical market data to predict future market trends and performance. Robo-advisors use this information to make informed investment decisions, providing clients with a competitive edge in the market. AI algorithms are used to monitor transactions and detect any fraudulent activity, helping to ensure the security and protection of clients' assets.

Using AI in robo-advisors is a significant step forward in the investment industry. The ability to provide personalized investment advice and portfolio management strategies, combined with the efficiency and accuracy of AI algorithms, makes robo-advisors an attractive option for individuals looking to manage their wealth. As technology continues to evolve, the use of AI in robo-advisors will likely become even more sophisticated and beneficial for clients.

However, the factors determining the adoption of robo-advisors vary greatly among investors. A systems dynamics model is a powerful tool for understanding the interrelated factors that influence the adoption of robo-advisors. This study aims to represent the various factors that influence the adoption of robo-advisors and how they interact.

The study is organized as follows. First, the paper reviews the literature on robo-advisors, including the benefits and challenges of adopting them, the factors influencing adoption, and previous research on the topic. Next, the paper presents the research methodology, addressing the design science approach and systems analysis modeling. The paper then discusses research design and model development. Subsequently, the paper presents candidate variables for a possible model extension. The future steps involving parameter estimation, scenario development, model validation, and model validation are detailed in the next section. Finally, the paper concludes the study, summarizing the main findings and implications of the research.

Literature review

Robo-advisors, also known as automated investment advisors, are a relatively new technology in the financial services industry. They use algorithms and artificial intelligence to provide investment advice to clients. The use of robo-advisors is rapidly increasing. This literature review aims to provide an overview of the current research on their adoption.

Several studies have focused on the factors that influence the adoption of robo-advisors. One key factor is the level of trust that clients have in the technology. For example, a study by Cheng et al. (2019) found that perceived trust significantly affects the adoption of robo-advisors. Similarly, a study by Guo et al. (2019) found that trust was a significant factor in adopting robo-advisors, particularly among those with limited experience with financial investments.

The perceived usefulness of the technology is another critical factor in adopting robo-advisors. A study by Moreno-García et al. (2019) found that perceived usefulness was a significant predictor of adoption intentions. Similarly, a study by Belanche et al. (2019) found that perceived usefulness and ease of use were salient factors in adopting robo-advisors. Investors are concerned about the performance of their portfolios and want to ensure that their investments deliver the best possible returns. Robo-advisors have a track record of providing competitive returns. However, investors must understand their historical performance and compare it to other investment options.

Another key factor driving the adoption of robo-advisors is their lower costs than traditional investment options (Ngo-Ye, Choi, & Cummings, 2018). Robo-advisors use algorithms and technology to manage portfolios, eliminating the need for human, financial advisors and reducing overhead costs. This translates into lower fees for investors, making it easier for people to invest their money and achieve their financial goals.

One of the primary advantages of using a robo-advisor is its convenience. With a few clicks, clients can create an account, answer questions about their investment goals and risk tolerance, and start investing. Unlike traditional financial advisors who require in-person meetings and phone calls, robo-advisors are accessible from anywhere with an internet connection. Research posited that usefulness and convenience are critical factors in a robo-advisors adoption model (Sabir, et al., 2023).

Despite the potential benefits of robo-advisors, some studies have identified potential barriers to adoption. For example, a study by Cheng et al. (2019) found that concerns about data privacy and security were a significant barrier to adoption, particularly among older investors. Similarly, a study by Jung et al. (2018) found that concerns about the lack of personal interaction with a human advisor were a significant barrier to adoption.

In addition, to trust and perceived usefulness, several studies have also examined the impact of demographic variables on adopting robo-advisors. For example, a study by Todd and Seay (2020) found that age, income, and education level were significant predictors of adopting robo-advisors. Similarly, a study by Fulk et al. (2018) found that younger investors were likelier to use robo-advisors than older investors.

In summary, adopting robo-advisors is influenced by several factors, including trust, perceived usefulness, and demographic variables. While robo-advisors have the potential to increase access to financial advice and improve investment outcomes, concerns about data privacy and the lack of personal interaction may hinder their adoption. The current study aims to understand how these factors interact and to identify strategies for increasing the adoption of robo-advisors, utilizing systems dynamics modeling and simulation as primary research vehicles.

Research methodology

The primary research methodology used in this paper is the design science research method (Hevner, March, Park, & Ram, 2008). Unlike social science research, which develops a model with hypotheses that can be statistically tested through controlled manipulation and empirical validation, the design science method aims to create information technology (IT) artifacts that solve specific organizational problems and undergo rigorous evaluation. This methodology involves identifying the problem, defining objectives for a solution, designing and developing appropriate IT artifacts, demonstrating the proof of concept, evaluating the effectiveness, and communicating the results. Adoption decisions on AI tools like robo-advisors are dynamic, making it challenging to assess the effectiveness of decisions and determine whether better decisions could have been made given the prevailing environmental conditions. Managers need a direct way of evaluating their decisions' effectiveness or identifying areas for improvement. This paper presents a model that allows managers to explore alternative strategies' effectiveness under different organizational and environmental conditions. The model serves as the artifact for the design science research method and provides an environment for investigating questions related to adoption decisions.

This section discusses different modeling techniques for examining the dynamic relationships between organizational constructs addressing the problem domain. The focus is on exploring the applicability of these techniques for modeling the problem and justifying the system dynamics approach as the preferred modeling approach for this paper. The available modeling techniques can be broadly categorized into optimization, heuristic search, and simulation (Choi, Nazareth, & Jain, 2013). Optimization is suitable for selecting the best solution from predefined alternatives (Chong & Żak, 2013). However, there are more effective techniques for problems involving a series of decisions over multiple time periods.

Additionally, the relationship between adoption decisions and environmental constructs is subject to discontinuities, making it difficult to apply standard optimization techniques. Heuristic search strategies, such as genetic algorithms (Holland, 1992), simulated annealing (Kirkpatrick, Gelatt Jr, & Vecchi, 1983), swarm optimization (Bonabeau, Dorigo, Theraulaz, & Theraulaz, 1999), and ant colony optimization (Dorigo, Maniezzo, & Colorni, 1996), have been developed to tackle these types of problems. These approaches apply real-world search strategies that improve the quality of the solution over successive iterations. However, these solutions are not guaranteed to be optimal.

Simulation, particularly system dynamics, is an effective alternative that permits the study of the phenomenon over time and leaves the tradeoff to the decision-makers. System dynamics (Forrester, 1994) combines discrete time periods and a set of difference equations to relate key variables within and across time periods, making it particularly well-suited to the repeated nature of the problem.

System dynamics traces its origins to systems of differential and difference equations, as noted in reference (Forrester, 1994). The models constructed in system dynamics consist of four key components: stocks, flows, converters, and connectors. These components are used to represent organizational processes, with stocks representing accumulations or depletions over time, typically in the form of tangible or intangible resources. Conversely, flows denote the change in stock levels, indicating resource utilization and replenishment over time. Stocks and flows follow conserving laws to ensure that future stock levels are based on current levels, moderated by any flows. Converters hold inputs, outputs, and intermediate values to perform computations without accumulating values. They are linked to other components via connectors, which represent information flows.

Feedback loops, both positive and negative, are essential in determining dynamic behavior, as most complex behaviors arise from feedback among the system components rather than from the complexity of individual components (Sterman, 2002). The construction and validation procedures in system dynamics are closely interwoven, with the initial identification of stocks and converters forming the basis of the model. The identification of stocks, converters, flows, and connectors is made through a series of textual analyses of published academic and professional literature, intentionally avoiding firm-specific data so that the experiments can be performed for various assumptions to generate organization-neutral implications.

Representing feedback processes is crucial in system dynamics modeling. Much of the art lies in discovering and modeling these feedback loops. The next step involves moving the causal diagram to a formal representation of the model, describing detailed relationships between causal links. Nonlinearities and discontinuities can easily be incorporated to ensure the model adequately reflects reality. The model is then applied to various organizational and environmental conditions to round out its development. When using the model, the emphasis is on analyzing behavior patterns, trends, and how quickly a variable achieves stability rather than on absolute values generated through the simulation.

Robo-advisor adoption model

The basis of the model lies in previous studies on the key factors that impact the adoption of robo-advisors. The four core factors have been identified from the extant literature review. Investors want to be sure that their robo-advisor is trustworthy, reliable, and has a strong reputation. Investors need to research the background of the robo-advisor and read reviews from other investors to ensure that they are comfortable with the service. Investors may be more likely to adopt robo-advisors if they trust the platform's technology and algorithms. On the other hand, investors who do not trust the technology or do not understand how the algorithms work may be less likely to adopt robo-advisors.

Several studies have shown that perceived usefulness is a significant factor in adopting robo-advisors. Investors who perceive robo-advisors as useful are more likely to adopt them as a tool for managing their investments. Several factors influence perceived usefulness, including ease of use, convenience, and the quality of advice.

The cost of using a robo-advisor is crucial in determining whether investors will adopt the technology. Many investors are attracted to the low fees associated with robo-advisors compared to traditional investment management services. This is because robo-advisors use computer algorithms to manage portfolios, eliminating the need for human investment advisors.

Robo-advisors are designed to be user-friendly and accessible, making it easier for investors to manage their portfolios from anywhere. This is particularly attractive to busy individuals who need more time or resources to manage their investments manually. One of the main factors driving the adoption of robo-advisors is their convenience and accessibility. With robo-advisors, clients can manage their investments anytime, anywhere, through a simple online platform. Clients can retrieve information about their portfolios and alter their investments with just a few clicks. The ease of use provided by this feature helps individuals keep track of their finances more efficiently and increases accessibility to investing, particularly for those who may have perceived the process as intimidating or too time-consuming.

Apart from the direct factors mentioned earlier, there are also environmental factors that can influence them. As an example, there is a set of demographic variables. Studies have shown that younger investors are more likely to adopt robo-advisors than older investors. This may be because younger investors are more familiar with technology and are more comfortable using digital platforms for financial services. On the other hand, older investors may prefer the personal touch of a traditional financial advisor. They may be less comfortable using technology for financial services. A study by Statista (2019) found that investors with higher income levels in the United States are more likely to use robo-advisors than those with lower income levels. One reason for this correlation could be that investors with higher income levels may have more disposable income to invest, making it easier to justify the fees associated with robo-advisors.

Additionally, investors with higher income levels may have more complex investment needs. They may find robo-advisors a more cost-effective solution than traditional financial advisors. Some demographic variables, such as income, affect the perceived usefulness.

It is essential for investors to carefully weigh these factors to ensure that they are making an informed decision and that the robo-advisor they choose is the right fit for their investment needs. Presented here is a preliminary version of a system dynamics model illustrating the adoption of robo-advisors:

- The stock of adopters (I) represents the number of investors who have adopted robo-advisors.
- The adoption rate (A) represents the rate investors adopt robo-advisors.
- The perception of cost (C) represents the perceived cost of using robo-advisors.
- The perception of convenience (V) represents the perceived convenience of using robo-advisors.
- The perception of usefulness (U) represents the perceived usefulness and performance of robo-advisors.
- The perception of trust (T) represents the perceived trustworthiness and reputation of robo-advisors.

The relationships between these factors can be represented as follows:

$$A = f\,(C, V, U, T)$$

Where f is a function that represents the factors' impact on the adoption rate.

For example, suppose the perception of cost is low, and the perception of convenience is high. In that case, the rate of adoption will be higher. Conversely, if the perception of cost is high and the perception of trust is low, the adoption rate will be lower.

Additionally, this study can represent the feedback loops between the stock of adopters and the perception of the various factors:

$$C = g(I)$$

$$V = h(I)$$

$$U = j(I)$$

$$T = k(I)$$

Where g, h, j, and k are functions representing how the stock of adopters influences the perception of the various factors. For example, if the stock of adopters is high, the perception of usefulness may be positive, leading to further adoption. Conversely, if the stock of adopters is low and the perceived trust is negative, the adoption rate may be slowed.

The system dynamics model offers a simplified depiction of the intricate and interdependent factors that impact the acceptance of robo-advisors. By applying this model, people can better comprehend the factors that propel acceptance and their interrelationships.

Environmental variables and model extension

Several other variables could be examined for future refinement and expansion. Security is a significant factor in the decision to adopt robo-advisors. Investors want to ensure that their personal and financial information is secure when using any online platform, including robo-advisors. Security concerns can include data breaches, identity theft, and other cyber-attacks. Robo-advisors have taken several measures to address security concerns, including data encryption, two-factor authentication, and secure servers. Additionally, robo-advisors are regulated by the Securities and Exchange Commission (SEC), which requires them to adhere to strict security protocols. Trust and reputation are closely linked to issues surrounding privacy and security.

Investment experience is another candidate factor that affects the adoption of robo-advisors. Investors with limited investment experience are more inclined to embrace robo-advisors as they might not possess the expertise or familiarity to make independent investment choices. Conversely, seasoned investors might opt to handle their investments themselves or may favor the customized guidance of a conventional financial advisor.

Investment goals also play a role in the adoption of robo-advisors. Investors with short-term investment goals may prefer the convenience and cost-effectiveness of robo-advisors. In contrast, investors with long-term investment goals may choose the personalized advice of a traditional financial advisor.

Risk tolerance can be another critical factor that affects the adoption of robo-advisors. Risk-averse investors may favor the convenience and cost-efficiency of robo-advisors. In contrast, those willing to undertake greater risk may opt for the tailored guidance of a conventional financial advisor.

After the present version of the model is completely implemented and validated, the factors mentioned above will be considered for its expansion.

Model validation and scenario development

System dynamics models are powerful tools for understanding complex systems and predicting their behavior. However, like any model, system dynamics models are only as good as their ability to represent the system they are meant to model accurately. This is where model validation comes in – testing the model's accuracy and reliability against real-world data.

System dynamics model validation involves several steps, including data collection (where real-world data that can be used to test the model's accuracy are collected), model calibration (the model's parameters to match the data better), sensitivity analysis (analyzing how sensitive the model's output is to changes in input variables), and validation testing (comparing the model's predictions to new data not used in the calibration step).

Step 1: Data collection

The first step in validating a system dynamics model is to collect real-world data that can be used to test the model's accuracy. This data should be collected from various sources, such as historical records, experiments, or surveys. The data quality is also essential; the data should be accurate, precise, and representative of the modeled system.

Step 2: Model calibration

Once the data has been gathered, the next step is to calibrate the model. This involves adjusting the model's parameters to match the data better. This step can be challenging, as a system dynamics model often has many parameters, and some may be difficult to measure directly. One approach is to use optimization techniques to find the set of parameter values that best match the data.

Step 3: Sensitivity analysis

After calibrating the model, the next step is to perform a sensitivity analysis. This involves testing how sensitive the model's output is to changes in input variables. This can help identify which variables are most important to the model's predictions and which parameters may need further refinement.

Step 4: Validation testing

The final step in the validation process is to test the model's predictions against new data not used in the calibration step. This is often the most critical step, determining how well the model can predict future behavior. If the model performs poorly on the validation data, it may need further refinement or modification.

Model validation is an essential step in the modeling process. It helps ensure that the model is accurate and reliable and that its predictions can be trusted. By following the steps outlined above and paying close attention to the quality of the data and the sensitivity of the model's predictions, the initial model drafts can be transformed into ones that yield valuable insights into intricate systems.

Utilizing the data gathered, a collection of differential equations will be formulated and examined through a sequence of pre-test scenarios. Once the model and equations can produce sensible and appropriate outcomes through model calibration, sensitivity analysis, and validation testing, a comprehensive set of scenarios will be developed. The model will then be implemented in a case scenario that examines the consequences of different strategies.

To validate the model and its framework, a multi-pronged evaluation approach described in this section will be taken. Once this is done, the modeling suite can be used to conduct a what-if analysis of various competing scenarios. The knowledge obtained from analyzing the simulation results will be precious when evaluating options for robo-advisors.

Conclusion

Many factors influence the adoption of robo-advisors. Understanding these factors is vital for financial institutions looking to enter the robo-advisor market and investors looking to make informed investment decisions. By considering these factors, financial institutions can tailor their robo-advisor offerings better to meet the needs of different types of investors. A systems dynamics model is a powerful tool for understanding the interrelated factors that influence the adoption of robo-advisors.

The financial industry is constantly evolving, and technology has led to the emergence of robo-advisors. Robo-advisors are digital platforms providing investment management services using AI algorithms, eliminating the need for human investment advisors. In recent years, the popularity of robo-advisors has increased, and many investors are considering the adoption of this technology for their investment needs.

However, the adoption of robo-advisors is a complex process that is influenced by multiple factors. To better understand this process, it is crucial to analyze the factors that influence the adoption of robo-advisors and how they interact with one another. This is where systems dynamics modeling can be helpful. Systems dynamics modeling is a systems thinking approach used to analyze complex systems and understand how different factors interact. In the context of robo-advisor adoption, systems dynamics modeling can be used to understand how factors such as cost, convenience, performance, trust, and customer service interact to influence the adoption of robo-advisors.

This report on the initial stages of the current study provides an overview of systems dynamics modeling and its application in the analysis of robo-advisor adoption. It explains the fundamental concepts of systems dynamics modeling and how it can be used to gain a deeper understanding of the factors that influence the adoption of robo-advisors. Subsequent stages will be carried out to finalize the model and scenarios, enabling the assessment of various strategies and analysis of managerial implications.

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