5-2018

Modeling Trust in the Adoption Decision Process of Robo-Advisors: An Agent-Based Simulation Approach

Sangho Lee
Kyobo Life Insurance Co., LTD., homosharus@gmail.com

Jae Choi
Pittsburg State University, jchoi@pittstate.edu

Thomas L. Ngo-Ye
Alabama State University, tngoye@alasu.edu

Maeve Cummings
Pittsburg State University, cummings@pittstate.edu

Modeling Trust in the Adoption Decision Process of Robo-Advisors: An Agent-Based Simulation Approach

Sangho Lee
Kyobo Life Insurance Co., LTD.
homosharus@gmail.com

Jae Choi
Pittsburg State University
jchoi@pittstate.edu

Thomas L. Ngo-Ye
Alabama State University
tngoye@alasu.edu

Maeve Cummings
Pittsburg State University
cummings@pittstate.edu

ABSTRACT

In recent years, financial technologies (FinTech) have been gaining increasing popularity. Although previous studies have glimpsed the role of Robo-Advisors as one potential source of cost saving and transparency in the financial service industry, it is still unclear whether Robo-Advisors will become a disruptive technology in the foreseeable future. Furthermore, there exists little work that examines fundamental questions regarding when and how Robo-Advisors can be successfully deployed. The dynamic nature and complexity of trust building mechanisms make these questions even more challenging. This study serves as a research-in-progress manuscript to report on the initial stages of a comprehensive study which aims to examine strategies for the implementation and deployment of Robo-Advisors.

Keywords

Financial technologies (FinTech), Robo-Advisors, IT adoption, diffusion, trust, agent-based modeling

INTRODUCTION

Digitalization has disrupted many service industries as exemplified in transportation (e.g. Uber) or the hospitality industry (e.g. Airbnb). The financial services industry is no exception, adopting potentially disruptive technologies ranging from automated teller machines to Robo-Advisors in recent years (Gold and Kursh 2017). Robo-Advisors offer investment advice using an algorithm-based process without human intervention (Gold and Kursh 2017). Robo-Advisors emerged as the latest FinTech after the 2008 financial crisis, in the wake of diminishing trust in traditional financial institutions (Gold and Kursh 2017; Salo 2017).

The adoption decision of a Robo-Advisor is strongly determined by trust as it is in any digitalization technology designed for service industries (Reichheld and Schefter 2000). Robo-Advisors offer investment advice using an algorithm-based process without human intervention (Gold and Kursh 2017). The primary benefits involved with Robo-Advisors are twofold; cost saving through a high degree of automation, and transparency through a consolidated user interface (Salo 2017). Within the context of Robo-Advisors, transparency is related to the feature that allows users to understand the entire situation so that a financial expert's interpretation or advice is not essential anymore. Although some research has been done on a few antecedents to trust, there is still much work left to do.

The dynamic nature and the complexity of trust building mechanisms as well as the emergence of new investment techniques make this investigation even more challenging. Considering the overall importance of FinTech in today's financial service industry, a model that captures the complexities of the problem domain while permitting a systematic exploration of alternative scenarios would be invaluable.

Adopting the design science research approach suggested in Gregor and Hevner (2013) and Peffers et al. (2008), which draw from ideas outlined in Hevner et al. (2004), this manuscript reports on the initial stages of the development of a dynamic Robo-Advisor trust model that captures the effects of alternative strategies involving the implementation of a Robo-Advisor. The subsequent steps planned will include a comprehensive analysis of simulation data generated by the proposed model.

TRUST AND ITS ANTECEDENTS

The current study seeks to accommodate the key antecedents of trust in the model since trust is generally regarded as an important precondition for the adoption of electronic services (Beldad et al. 2010). One critical trust antecedent in FinTech tools is their security and privacy features. Users view security features as vital criteria in the assessment of trustworthiness (Aiken and Bousch 2006). The importance of security and privacy features is more pronounced in the financial service industry because financial information is one of the main targets of fraud (Roca et al. 2009). Security breaches are only worsening as consumers need more access to data and applications. A variety of security tools and techniques are available to implement the five categories of security controls; authentication control, non-repudiation control, privacy control, confidentiality control and data integrity control (Ray et al. 2011). The successfully implemented tools and techniques lead to perceived better security.

Another key antecedent to trust in FinTech tools is information quality (Beldad et al. 2010). Information quality may refer to a variety of concepts including error-freeness (Bart et al. 2005), accuracy, currency, and completeness of information (Kim et al 2005), and correctness in spelling, grammar, and syntax (Koehn 2003). The content quality increases customers' trust in using an electronic service. Information quality is considered even more critical in Robo-Advisors as the performance of the advised portfolio relies on it.

Financial advisors consider Robo-Advisors to be a suitable tool to manage smaller accounts partially due to the low cost involved with Robo-Advisors. Customers with larger accounts are less concerned with advising cost than with flexibility. A more pressing reason would be, however, that Robo-Advisors have failed to demonstrate a superior level of performance in sizable portfolios. More advanced artificial intelligence algorithms might shift the horizon and help wealth managers respond more dynamically to customers' needs. As sophisticated algorithms become available, it will be possible to accommodate investment techniques like factor-based investing, which is rarely embedded in extant Robo-Advisors.

Finally, experience and proficiency in Internet usage may play a critical role in developing trust in electronic services as evidenced by one study (Corbitt et al. 2003). Echoing this, Reuba suggests that a higher impact from Robo-Advisors is expected as millennials earn more money to invest (Reuba 2017).

METHODOLOGY

A primary objective in the current study is the predictive capability of the dynamic Robo-Advisors trust model. For this study a modeling approach is being adopted since conventional social science research methodology is more suitable for investigating cause and effect relationships. This approach lends itself to the examination of the dynamic impact of Robo-Advisors implementation strategies under a variety of conditions. The design science approach mandates the utilization of an IT artifact that can be studied under a variety of conditions. Since the trust building mechanism in Robo-Advisors is dynamic in nature, the artifact proposed in this research is a model suite that will allow decision makers to assess the impact of alternative decisions regarding Robo-Advisors implementation under varying conditions. Simulation can capture the dynamic relationship between constructs relevant to the problem over time.

Given that the Robo-Advisors implementation involves an environment of multiple interacting agents and constructs, an agent-based modeling approach is preferred. Agent-based modeling is a computational simulation approach that permits the study of phenomena over time (Bonabeau 2002). Agents are entities of the system which generate autonomous behaviors. Once the behavior of an individual agent is prescribed, the effectiveness of its logic is accessed by interacting operators (Ngo-Ye et al. 2017). The problem can be examined over multiple time periods based on the prevailing conditions.

MODEL DEVELOPMENT

The model being developed is based on the Dynamic Security-Trust Lifecycle model (Choi and Nazareth 2014). The Dynamic Security-Trust lifecycle model captures the role of trust in dynamic interactions between electronic service vendors and customers, providing the fundamental features of the current study. An extensive set of modifications, recalibrations, and extensions will be provided to ensure that the model reflects the additional core antecedents to trust in Robo-Advisors; information quality, and experience/proficiency in Internet usage.

The number of both Robo-Advisors and customers can be adjusted, allowing decision makers to simulate the different conditions of the financial service industry where multiple Robo-Advisors are offered to many customers. Robo-Advisors are available at different price points from multiple providers. Moreover, average attractiveness throughput is a user adjustable value which represents the favorability of adopting the Robo-Advisors service in general. The two main factors influencing the choice of Robo-Advisors are price and trustworthiness. Price affects the market share of each Robo-Advisor, and eventually, the competitive advantage against incumbent financial advisors. Another critical factor is trustworthiness. It is determined by the combined level of initial and ongoing trust. The initial trust is shaped by the customer's perceptions based on reputation and brand (Lynn et al. 2016; Pearson and Yee 2013). Ongoing trust fluctuates due to security and privacy related events in data transactions, data handling, data usage, and other factors related to security/privacy mismanagement. Offense and offense severity in the current prototype concern security breaches exclusively. Information quality represents the eventual outcome quality of Robo-Advisors' digital service. Therefore, investment performance is included as a part of information quality. Furthermore, the effective size of a portfolio is directly related to its investment performance. As more sophisticated algorithms are capable of accommodating advanced investment techniques like factor-based investing, the flexibility of the algorithm is enhanced. In other words, as Robo-Advisors become more powerful and flexible, they approach the capability of human financial advisors. Hence, the flexibility of an algorithm is strongly related to investment performance, which is a dimension of information quality. We are in the process of accommodating information quality factors in ongoing and initial trust building mechanisms. The information quality degradation will be reflected in offense and offense severity. The dimensions of information quality include the transparency of information, the level of data consolidation, investment performance, the effective size of the portfolio, and the flexibility of the algorithm. Investment performance affects trust forming in the form of previous historical performance data provided by the Robo-Advisors service vendor as a marketing pitch or overall industry performance comparison data, or consumer testimonials. The current stage of the model interface is depicted in Figure 1. All the current features in the model are related to security breaches and recovery referenced in Choi and Nazareth (2014). Workstation shaped agents represent Robo-Advisors while person shaped agents represent customers. Red colored figures signify customers who are currently using a Robo-Advisor, while blue colored figures denote customers who are not currently using any Robo-Advisors.

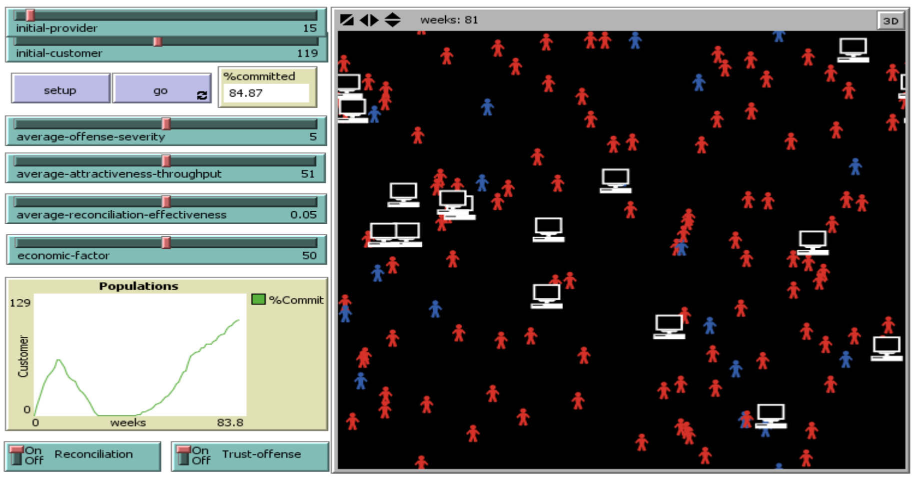

Figure 1. The Dynamic Trust Model for Robo-Advisors

FUTURE PLANS AND CONCLUDING REMARKS

This manuscript presents a set of initial steps, based on theoretical underpinnings, for developing a dynamic model that examines the role of trust and its antecedents in the implementation strategies of Robo-Advisors. The subsequent stages will be as follows: We are currently in the process of accommodating information quality factors in initial and ongoing trust building mechanisms. The next stage involves the representation of experience in Internet usage within the model. Once the model generates reasonable behavior, a complete set of scenarios will be developed and analyzed to discover the implications of alternative strategies and conditions. The insights gained through the analysis of the simulation outcomes should prove priceless to financial advisors when evaluating Robo-Advisors' implementation decisions.

REFERENCES

1. Aiken, K. D. and Bousch, D. M. (2006) Trustmarks, objective-source ratings, and implied investments in advertising: Investigating online trust and the context-specific nature of internet signals, *Journal of the Academy of Marketing Science*, 34, 308-323.
2. Bart, Y., Shankar, V., Sultan, F., and Urban, G. L. (2005) Are the drivers and role of online trust the same for all web sites and consumers? A large-scale exploratory empirical study, *Journal of Marketing*, 69, 133-152.
3. Beldad, A., De Jong, M., and Steehouder, M. (2010) How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust, *Computers in Human Behavior*, 26, 857-869.
4. Bonabeau, E. (2002) Agent-Based Modeling: Methods and Techniques for Simulating Human Systems, *Proceedings of the National Academy of Science*, 99, 3, 7280-7287.
5. Choi, J., and Nazareth, D. L. (2014) Repairing trust in an e-commerce and security context: an agent-based modeling approach, *Information Management and Computer Security*, 22, 5, 490-512.

6. Corbitt, B. J., Thanasankit, T., and Yi, H. (2003) Trust and e-commerce: A study of consumer perceptions, *Electronic Commerce Research and Applications*, 2, 203-215.
7. Gold, N. A. and Kursh S. R. (2017) Counterrevolutionaries in the Financial Service Industry: Teaching Disruption-A Case Study of RoboAdvisors and Incumbent Responses, *Business Education Innovation Journal*, 9, 1, 139-146.
8. Gregor, S. and Hevner, A. R. (2013) Positioning and Presenting Design Science Research for Maximum Impact, *MIS Quarterly*, 37, 2, 337-355.
9. Hevner, A. R., March, S. T., Park, J. and Ram, S. (2004) Design Science in Information Systems Research, *MIS Quarterly*, 28, 1, 75-105.
10. Kim, D. J., Song, Y. I., Braynoy, S. B., and Rao, H. R. (2005) A multidimensional trust formation model in B-to-C e-commerce: A conceptual framework and content analyses of academia/practitioner perspectives, *Decision Support Systems*, 40, 143-165.
11. Koehn, D. (2003) The nature of and conditions for online trust, *Journal of Business Ethics*, 43, 3-19.
12. Lynn, T., van der Werff, L., Hunt, G., and Healy, P. (2016) Development of a Cloud Trust Label: A Delphi Approach, *Journal of Computer Information Systems*, 56, 3, 185-193.
13. Ngo-Ye, T., Nazareth, D. L., and Choi, J. (2017) Trust in Cloud Computing: Maintaining Long-Term Relationships, *Journal of Information Technology Management*, 28, 3, 25-38.
14. Pearson, S. and Yee, G. (2013) Privacy and Security for Cloud Computing: Computer Communications and Networks, Springer-Verlag, London, UK
15. Peffers, K., Tuunanen, T., Rothenberger, M. A. and Chatterjee, S. (2008) A Design Science Research Methodology for Information Systems Research, *Journal of Management Information Systems*, 24, 3, 45-77.
16. Ray, S., Ow, T. and Kim, S. (2011) Security assurance: how online service providers can influence security control perceptions and gain trust, *Decision Sciences Journal*, 42, 2, 391-412.
17. Reichheld, F. F. and Schefter, P. (2000) E-Loyalty: Your Secret Weapon on the Web, *Harvard Business Review*, 78, 4, 105-114.
18. Reuba, K. (2017) Robo-Advisors: Early Disruptors in Private Wealth Management. Allianz Investment Themes and Strategy, https://www.allianzgi.com/home/insights/artificial-intelligence/robo-advisors-early-disruptors-in-private-wealth-management
19. Roca, J. C., Carcia, J. J., and de la Vega, J. J. (2009) The importance of perceived trust, security and privacy in online trading systems, *Information Management and Computer Security*, 17, 2, 96-113.
20. Salo, A. (2017) Robo Advisor, Your Reliable Partner? Building A Trustworthy Digital Investment Management Service, Master’s Thesis, School of Management, University of Tampere, Tampere, Finland.