Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2019 Proceedings

DLT, Blockchain and FinTech

Determinants and Barriers of Adopting Robo-Advisory Services

Maike Bruckes
University of Muenster, maike.bruckes@wiwi.uni-muenster.de

Daniel Westmattelmann
University of Muenster, daniel.westmattelmann@wiwi.uni-muenster.de

Andreas Oldeweme
University of Muenster, andreas.oldeweme@wiwi.uni-muenster.de

Gerhard Schewe
University of Muenster, gerhard.schewe@wiwi.uni-muenster.de

Determinants and Barriers of Adopting Robo-Advisory Services

Short Paper

Maike Bruckes
Center for Management
University of Muenster
Universitätsstraße 14-16
48143 Muenster
maike.bruckes@wiwi.uni-muenster.de

Daniel Westmattelmann
Center for Management
University of Muenster
Universitätsstraße 14-16
48143 Muenster
daniel.westmattelmann@wiwi.uni-muenster.de

Andreas Oldeweme
Center for Management
University of Muenster
Universitätsstraße 14-16
48143 Muenster
andreas.oldeweme@wiwi.uni-muenster.de

Gerhard Schewe
Center for Management
University of Muenster
Universitätsstraße 14-16
48143 Muenster
gerhard.schewe@wiwi.uni-muenster.de

Abstract

Robo-advisors enable customers to conduct automated digital investments, which could substantially transform the financial industry. However, robo-advisory use is lagging behind expectations. One reason could be potential customers' insufficient trust.

Therefore, we investigate determinants that influence trust and the intention to use robo-advisors. More specifically, we build on trust to assess use intention and explore personal characteristics (perceived risk), organizational characteristics (trust in banks) and industry characteristics (structural assurances) as antecedents to trust. The survey data are analyzed by employing a PLS-SEM (n = 246).

Preliminary results show that initial trust in robo-advisors is closely related to the intention to use robo-advisors. Trust is negatively linked to perceived risk but positively linked to structural assurances. Trust in banks is positively related to initial trust, however, only when structural assurances are not included. In a follow-up survey, behavior and potential barriers to robo-advisory adoption will be investigated.

Keywords: Robo-advisory, trust, risk, structural assurances

Introduction

The application of smart systems and algorithm-based decisions has the potential to reform the financial sector and poses an enormous challenge, particularly for conventional banks. A vivid example of this is the use of robo-advisors. Robo-advisory is a financial service that combines investment advisory with algorithm-based investment decisions. In contrast to classic personal customer advice, personal contact between the customer and the bank is completely eliminated by the use of robo-advisors (Jung et al. 2018a). The customer is guided through questions, e.g., about the customer's personal situation and risk tolerance, to an individual investment proposal (Phoon and Koh 2017).

Banks are eager to use robo-advisors as an automated investment advisory to reach further customers. Especially because of their cost-saving design, robo-advisors are also well suited to target customers with smaller budgets than those required for traditional investments (Jung et al. 2018a). However, these customers show particularly high risk aversion (Epperson et al. 2015; Jung et al. 2018a).The perceived risks of using robo-advisory can be explained by a low level of perceived user control during the investment process (Rühr et at. 2019). Accordingly, it is not surprising that the acceptance rate of robo-advisory is relatively low, with less than 0.1% of assets under management managed by robo-advisory services in 2018 worldwide (Statista 2019). Nevertheless, future prospects are highly promising, with forecasts predicting that by 2020, these services will manage 10% of total assets globally (BI Intelligence 2017). Thus, the issue of digital transformation has become the most important challenge for the future strategic orientation of banks.

However, banks are not the only players in this market. New entrants such as financial technology startups (Fintechs) or technology companies are increasingly forcing their way into this market (Du Toit and Cheris 2018). Against the background of their enormous success, this represents a high threat for established banks. Studies show that 54% of customers would rather use banking services provided by technology companies than those provided by banks (Bain & Company 2018). As a result, banks are no longer in competition only with each other but rather are also in competition with Fintechs and other technology companies.

Nevertheless, banks have the advantage of having established relationships with their customers. Banks know the regulations in the financial sector and already hold or manage their customers' financial assets. Above all, they already have their customers' trust. While trust in financial institutions has been rather low in the last decade, it has experienced a rise in recent years (Edelman 2018). Banks have realized that their customers' trust is a decisive factor for the success of their digitalization strategies. Research has supported this view, showing that trust is one of the most important factors for the acceptance of financial online services and as such might also positively influence robo-advisory service adoption (Baptista and Oliveira 2016; Chiu et al. 2017). However, research has also shown that structural assurances in the form of appropriate technological and legal structures have a strong effect on initial trust in technologies (McKnight et al. 2011; Pavlou and Gefen 2004). Such structural assurances can be provided irrespective of whether a bank or a technology company offers the robo-advisory service. Therefore, it is questionable whether customers' trust in banks provides an advantage for banks to successfully promote the use of robo-advisors.

To investigate these issues, we aim to address the following research questions: Which determinants influence the adoption of robo-advisors? How does trust in banks and structural assurances affect trust in robo-advisors? To address these questions, we conduct a PLS-SEM (n =246). We contribute to the literature by shedding light on the determinants and barriers to the adoption of robo-advisors. While trust has been shown to be decisive for other financial online services, the relationship has not been sufficiently investigated in the context of robo-advisory. In the further progress of this research project, the relationship between the intended and actual uses of robo-advisory will be the focus. In particular, the barriers of actual use are to be investigated to derive further valuable implications for practice.

The paper is organized as follows. The next section presents a brief overview of recent research in the literature on the adoption of robo-advisory. We develop hypotheses and present our research model in the subsequent section. We then describe our methodological approach and research results. Finally, the article continues with a discussion of the results and their implications and finishes with an outlook for future research.

Theoretical Foundation and Research Model

Literature Review

As the literature on robo-advisory is only emerging, few researchers have focused on this issue yet. Previous research has drawn on related areas such as financial advisory research and decision support literature (Jung et al. 2018b). Studies on customers' willingness to interact with robo-advisors have investigated the influence of robo-advisor designs (Glaser et al. 2019; Jung et al. 2018a; Kilic et al. 2015; Ruf et al. 2015) or the impact of personalization as an essential feature of robo-advisors (Faloon and Scherer 2017). Other studies have focused on legal complexities (Ji 2017) and risk management aspects (Glaser et al. 2019).

Considering consumer behavior, Lee et al. (2018) emphasize the relevance of trust in the adoption of robo-advisory. Based on an agent-based model, they propose that trust and information quality are critical components of the adoption process. These findings are in line with Jung et al.'s (2018a) interview study, where participants reported that the impression of trustworthiness was one of the major factors in their attitude towards a robo-advisor. In another study on robo-advisory, Jung et al. (2018b) review the literature on robo-advisory and conclude that trustful communication is at least as important as the performance of robo-advisors. Taken together, these studies indicate that trust is a strong predictor of robo-advisory adoption.

One critical antecedent to trust is the perceived risk associated with the technology. Studies that have investigated this relationship have found strong support for this link (Malaquias and Hwang 2016; Roca et al. 2009). Perceived risk is especially important in the robo-advisory context because financial information is often used for fraud, and customers often feel uncertain when making financial decisions (Heinrich and Schwabe 2018; Roca et al. 2009). Thus, it can be assumed that the risk associated with robo-advisory is perceived to be higher than that associated with traditional investments. The transaction is mediated by technology, and the customer needs to make decisions more independently. Thus, while the customer previously consulted a bank advisor while making an investment, the customer now has to take on additional responsibility (Rühr et al. 2019).

Additionally, previous research has emphasized the relevance of customers' trust in firms and structural assurances for trust development (Kim et al. 2009; Kundu and Datta 2015; Zhou 2012). As no personal contact with any advisor is given when using robo-advisors, the company that offers the robo-advisor, often a bank, serves as the only other referent of trust (Jung et al. 2018a). Structural assurances are concerned with feeling a sense of security as opposed to perceiving risk because of institutional arrangements (Moin et al. 2015). Kim and Prabhakar (2004) show that structural assurances are significant predictors of initial trust in electronic channels as a banking medium. Thus, trust in the bank and structural assurances have been identified as antecedents to trust in financial technologies. In summary, these studies indicate that trust in banks, structural assurances and perceived risk are closely linked to trust in robo-advisors, which is seen as a critical determinant for the intention to use robo-advisors.

Research Model

Trust

Trust comprises the willingness to be vulnerable based on positive expectations towards a technology (McKnight et al. 2011). A number of previous studies have confirmed the positive relationship between trust in technologies and usage intention (Dimitriadis and Kyrezis 2010; Gefen et al. 2003; Kim and Prabhakar 2004). For the adoption of robo-advisory technology, trust might be equally important. If customers believe that robo-advisors are reliable and perform well and thus have trust in them, they are more likely to actually use them. Accordingly, the following hypothesis is formulated:

H1: Initial trust in robo-advisors is positively related to the intention to use them.

Many customers feel uncertain when conducting digital investments for the first time (Zhou 2012). To overcome uncertainty, customers' trust may be especially relevant in this situation. Trademark perception suggests that the trust positively associated with a brand is transferred to other services via the recognition of a brand. If a customer notices the well-known and positively rated brand of a bank, a subconscious transfer of trust to the new products and services offered takes place (Lee et al. 2007). This notion is supported by previous studies that showed a positive effect of a bank's image on customers' confidence in the bank's online products (Flavián et al. 2005; Yap et al. 2010). If customers perceive the bank as competent in areas such as online banking and traditional investments, they might assume that the bank is also competent in designing reliable robo-advisory services. Thus, customers might transfer the trust they have in the bank to the robo-advisors. Therefore, we argue as follows:

H2: Customer trust in banks is positively related to initial trust in robo-advisors.

Perceived Risk

The use of a new technology in general and in a digital context in particular is associated with an inherent risk. This risk is based on uncertainty about the outcome but might also be due to fear of losing money or private data during the configuration process (Forsythe and Shi 2003; Malaquias and Hwang 2016). The riskier a customer perceives the use of robo-advisors to be, the lower the initial trust and the intention to use robo-advisors (Forsythe and Shi 2003). These relationships have been examined in other contexts. For example, Jarvenpaa et al. (2000) show that a higher risk perception reduces the willingness to buy books online. Malhotra et al. (2004) indicate a negative correlation between perceived risk and the willingness to disclose personal information on the internet. Kesharwani and Singh Bisht (2012) show that fear of insufficient protection of technological infrastructure negatively influences the intention to use online banking. Based on these theoretical explanations and the empirical findings, the following hypotheses are formulated:

H3: Perceived risk is negatively related to the intention to use robo-advisors.

H4: Perceived risk is negatively related to initial trust in robo-advisors.

Structural Assurances

In contrast to transactions in an analogue context, the digital environment often lacks common trust-generating features. While in a bank branch, for example, customers can convince themselves of the professional behavior of employees or the appearance of the building, similar features are often missing on the internet. Against this background, there are other factors – so-called structural assurances – that can also build trust online (Zhou 2012). Structural assurances can be safety mechanisms as guarantees and laws or other structures that enhance perceived security (Kim and Prabhakar 2004). These structural assurances are especially relevant at the beginning of a new relationship and when the information base is imperfect (McKnight et al. 1998). Accordingly, it can be expected that structural assurances decrease perceived risk by reducing safety concerns (Luo et al. 2010). In addition, structural assurances contribute to robo-advisors being perceived as trustworthy. In line with studies investigating this relationship (e.g., Kim and Prabhakar 2004; Luo et al. 2010; Yap et al. 2010), the following two hypotheses are proposed:

H5: Structural assurances are negatively related to the perceived risk of robo-advisors.

H6: Structural assurances are positively related to initial trust in robo-advisors.

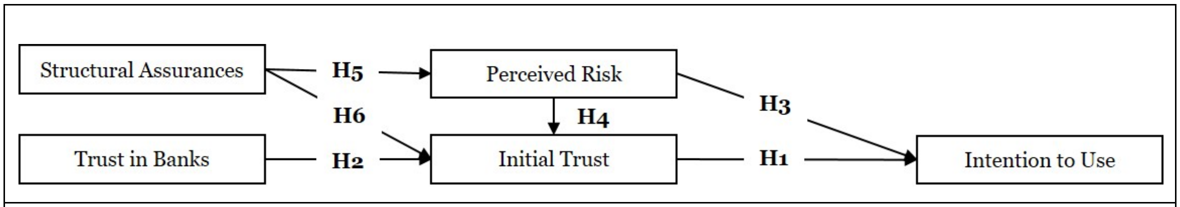

Figure 1. Proposed Research Model

Empirical Study

Design and Participants

During the course of the questionnaire, the participants were familiarized with the concept of robo-advisory. For this purpose, we first gave information about robo-advising, including facts and an explanation of the basic functionality. In a second step, an investment process via a robo-advisor was simulated. In this simulation, the participants had to go through the first steps of a digital investment decision by answering questions about their potential investment (e.g., their attitude towards risk and the time horizon). The aim was to convey a realistic impression of the digital investment process. After the participants had completed this process, they answered the questionnaire. These questionnaires serve as the data basis for this analysis.

During data collection, 331 subjects completed the questionnaire. Due to missing data or incorrect answers to the control question, 85 had to be excluded from the analysis, resulting in 246 completed questionnaires. Of the final sample, 127 participants (52%) were female, and on average, the participants were 36 years old, with a range from 18-63 years. Overall, 118 (48%) of the participants had a higher education degree.

Measurements

The research model used established scales that have been validated in previous studies. All questions were measured on a 5-point Likert scale. Intention to use was measured on a three-item scale (Cronbach's alpha (α) = .937, composite reliability (CR) = .960, average variance extracted (AVE) = .889). For initial trust in the robo-advisor, we built on the scale developed by Zhou (2012; α = .875, CR = .915, AVE = .731). To measure trust in banks, we modified a four-item scale of Suh and Han (2002; α = .894, CR = .925, AVE = .754). Perceived risk was measured using a scale developed by Dash and Saji (2008; α = .794, CR = .859, AVE = .554), and items for structural assurances were adapted from McKnight et al. (2002) and Kim et al. (2009; α = .826, CR = .885, AVE = .658). All factor loadings exceed .60 and therefore show acceptable values (Hair et al. 2016). We included the demographic variables sex, education, and income as controls.

Before conducting the SEM, we tested the reliability and validity of the measurement model. Internal consistency and composite reliability can be assumed since Cronbach's alpha met the quality criteria of >0.7 and the AVE exceed .50 (Hair et al. 2016). To ensure discriminant validity, we examined the Fornell-Larcker and the Heterotrait-Monotrait (HTMT) criterion. The results show that the square root of each AVE in the diagonal is greater than the squared correlation between any pair of constructs, and all HTMT ratios are below the threshold of .90, confirming the discriminant validity of the measurement model (Fornell and Larcker 1981; Hair et al. 2016). Finally, all variance inflation factor (VIF) values are below 3, which suggests that multicollinearity is not an issue (Hair et al. 2016).

Results

We conducted the analysis using PLS-SEM as this method does not impose distributional assumptions on the data and is well suited for novel contexts (Hair et al. 2019). Table 1 shows the results of the PLS-SEM. We conducted the analysis in two steps to better understand the relationship between trust in banks and structural assurance. Consequently, the models differ in terms of the inclusion of structural assurance. Model 1 considers only consumers' trust in banks and risk, while model 2 also includes structural assurances. Control variables were included in both models but did not show significant influences.

To select the best fitting model, we used several model selection criteria derived from information theory. These criteria include the asymptotically efficient Unbiased Akaike's Information Criterion (AICu; Akaike 1973), the asymptotically consistent Bayesian Information Criterion (BIC; Schwarz 1978), the Hannan-Quinn Criterion (HQ) and the Corrected Hannan-Quinn Criterion (HQc; McQuarrie and Tsai 1998). We then created a set of theoretically plausible models and calculated their selection criteria values. Based on these selection criteria, we compared the alternative models and selected the one that showed the best model selection criteria values (Hair et al. 2019; Sharma et al. 2018).

This resulted in the selection of models 1 and 2, whose PLS criteria we then examined. Both models show that the explained variance (adj. R^2) and the predictive relevance (Q^2) are satisfactory for initial trust (adj.

$R^2_{Model\ 1}$ = .251, adj. $R^2_{Model\ 2}$ = .306, $Q^2_{Model\ 1}$ = .172, $Q^2_{Model\ 2}$ = .212) and intention to use (adj. $R^2_{Model\ 1}$ = .443, adj. $R^2_{Model\ 2}$ = .440, $Q^2_{Model\ 1}$ = .375, $Q^2_{Model\ 2}$ = .373).

Model 1 finds support that trust in robo-advisors is positively related to usage intention, which supports H1 (β = .633, p <.001), and trust in banks is positively related to trust in robo-advisors, supporting H2 (β = .149. p <.001). Perceived risk is not significantly related to the intention to use robo-advisors (β = -.091, p = .108). Thus, H3 must be rejected. However, risk is negatively related to trust in robo-advisors, supporting H4 (β = -.470, p < .001).

Model 2 shows results including structural assurance. The results support H5, which proposed that structural assurances is negatively related to perceived risk (β = -.431, p <.001). H6, which stated that structural assurances is positively related to trust in robo-advisors, is also supported (β = .286, p <.001). However, when structural assurances is included, the effect of trust in banks on trust in robo-advisors diminishes (β = .039, p =.558). Thus, with all variables included, H2 must be rejected.

Table 1. Results PLS-SEM

	Model 1		Model 2		
	H1 – H4		H1 – H6		
	IN	IT	IN	IT	PR
Initial Trust (IT)	.633*** (.047)		.635*** (.047)		
Trust in Banks		.149*** (.053)		.039 (.053)	
Perceived Risk (PR)	-.091 (.056)	-.470*** (.050)	-.084 (.057)	-.363*** (.060)	
Structural Assurances				.286*** (.068)	-.431*** (.058)
adj. R^2	.443	.251	.440	.306	.177
Q^2	.375	.172	.373	.212	.085
AICu	-65.044	-129.776	-85.964	-135.925	-45.853
BIC	-57.547	-112.341	-71.942	-111.387	-38.843
HQ	-63.828	-126.998	-80.318	-126.045	-43.031
HQc	-63.616	-126.091	-79.977	-125.138	-42.918

Table 1. Results PLS-SEM

Note. Standardized path coefficients. Standard error of the estimators in parentheses. IN = Intention to Use; AICu = Unbiased Akaike's Information Criterion; BIC = Bayesian Information Criterion; HQ = Hannan-Quinn Criterion; HQc = Corrected Hannan-Quinn Criterion; *$p \leq .05$; **$p \leq .01$; ***$p \leq .001$.

Discussion

The aim of this study was to investigate the relationship between trust and the intention to use robo-advisors for investments. Our results indicate that initial trust in robo-advisors is a strong predictor of use intention. Therefore, factors that influence initial trust are of critical importance.

Model 1 showed that trust in banks is positively related to trust in robo-advisors. Thus, customers who have high trust in banks are more likely to trust robo-advisors. Banks provide guidance to customers, perhaps because they provide an environment with which customers are familiar. However, as model 2 shows, trust in banks can, at least partially, be substituted by structural assurances. Thus, initial trust in robo-advisors can also be developed by structural assurances. When customers feel that they can use robo-advisors in an environment they feel comfortable in, trust in banks is no longer decisive. Banks must provide additional benefits to compete with technology companies, as they cannot rely on their customers' trust alone. Such benefits can be based on the bank's expertise in financial markets, on their providing guidance that is more competent and comprehensive during the investment process or on their better connecting individual services. Further, banks need to strengthen their capabilities in the areas that provide structural assurances, such as privacy, security, and reliability, to successfully participate in the digital investment market. Technology companies will continue to push into this market and challenge the established players. Structural safeguarding seems to be the most important factor considering the implementation of trust in robo-advising. The use of robo-advisors is inherently risky. Perceived risk has a negative effect on consumers' trust in robo-advisors but, interestingly, no effect on use intention. Thus, trust mediates the relationship between perceived risk and use intention. This indicates that customers accept the risk but intend to use robo-advisors only if their trust is high enough.

Extended Research Model

While the preliminary results of this study provide promising insights for the full-scale project, some questions remain unanswered. The intention to use robo-advisors does not necessarily lead to actual use (Venkatesh et al. 2003). Therefore, we aim to conduct a follow-up study to ask participants about their actual behavior to extend the proposed research model. To obtain meaningful results on the outcome of the active adoption decision-making process, we aim for a time gap of one year between the two survey periods (Venkatesh et al. 2003). In addition to assessing actual behavior, we are also interested in barriers to the adoption decision. Some participants may perceive a lack of accessibility due to insufficient information or the lack of an overview of various offers. Other participants may be inert towards change or regard performance expectations as inappropriate, which both can be decisive barriers to robo-advisory use.

To address these issues regarding the intended and actual uses of robo-advisory at ICIS 2019, we will conduct a follow-up survey in August 2019. A power analysis with G*Power 3.1 was performed to determine the required sample size for analyzing actual usage behavior (Faul et al. 2007). A meta-analysis revealed that the average effect between use intention and the actual use of mobile banking is .427 (Baptista and Oliveira 2016). As the barriers to the use of robo-advisors might be higher than the barriers to mobile banking, we assumed medium effect sizes (~.15) for the power analysis to estimate the sample size conservatively (Cohen 1988). Using a two-tailed test with an alpha error of .05 and a power of .80, the projected minimum sample size needed for the second survey is approximately N = 55. This proposed sample size for the follow-up study also exceeds the requirements formulated by Hair et al. (2016). Given the 246 participants in the first survey stage, it seems highly realistic that at least 55 (22.3% response rate) of these participants will also participate in the second survey. In view of the expected low proportion of actual users (BI Intelligence 2017), this number of participants is also sufficient to determine the barriers to use. In the first step, structured questions are used to examine possible barriers. In the second step, further barriers are queried through open questions in case the selection in the first step is not exhaustive.

The final study will provide evidence on enabling and hindering mechanisms to robo-advisory adoption. Based on the two-step data collection, the final study will provide theoretical explanations and empirical validations of the differences between adopters of robo-advisory services and non-adopters. Moreover, we will be able to offer specific recommendations for practitioners to enhance the adoption of robo-advising.

References

Akaike, H. 1973. "Information theory and an extension of the maximum likelihood principle," in *Second lnternational Symposium on Information Theory*, B. N. Petrov, and E. Caski (eds.), Budapest, Hungary, pp. 267–281.

Bain & Company 2018. *Banks underperform in five out of five categories that matter most to customers—and technology firms are circling*. Bain & Comp. (https://www.bain.com/about/media-center/press-releases/2018/loyalty-in-banking, accessed 18 April 2019).

Baptista, G., and Oliveira, T. 2016. "A weight and a meta-analysis on mobile banking acceptance research," *Computers in Human Behavior* (63), pp. 480–489.

BI Intelligence 2017. *The Robo-Advising Report*. (https://www.businessinsider.com.au/the-robo-advising-report-market-forecasts-key-growth-drivers-and-how-automated-asset-management-will-change-the-advisory-industry-2016-6, accessed 18 April 2019).

Chiu, J. L., Bool, N. C., and Chiu, C. L. 2017. "Challenges and factors influencing initial trust and behavioral intention to use mobile banking services in the Philippines," *Asia Pacific Journal of Innovation and Entrepreneurship* (11:2), pp. 246–278.

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*, Hillsdale, NJ: Erlbaum.

Dash, S., and Saji, K. B. 2008. "The Role of Consumer Self-Efficacy and Website Social-Presence in Customers' Adoption of B2C Online Shopping," *Journal of International Consumer Marketing* (20:2), pp. 33–48.

Dimitriadis, S., and Kyrezis, N. 2010. "Linking trust to use intention for technology-enabled bank channels: The role of trusting intentions," *Psychology and Marketing* (27:8), pp. 799–820.

Du Toit, G., and Cheris, A. 2018. *Can Amazon Take Customer Loyalty to the Bank?*. Bain & Comp. (https://www.bain.com/insights/can-amazon-take-customer-loyalty-to-the-bank/, accessed 18 April 2019).

Edelman 2018. Edelman Trust Barometer. (https://www.edelman.com/sites/g/files/aatuss191/files/2018-10/Edelman_Trust_Barometer_Financial_Services_2018.pdf, accessed 7 April 2019).

Epperson, T., Hedges, B., Singh, U., and Gabel, M. 2015. "Hype vs. Reality: The Coming Waves of "Robo" Adoption. Robo-Advisory Services Study," A. T. Kearney. (https://www.atkearney.com/documents/10192/7132014/Hype+vs.+Reality_The+Coming+Waves+of+Robo+Adoption.pdf, accessed 16 August 2019).

Faloon, M., and Scherer, B. 2017. "Individualization of Robo-Advice," *The Journal of Wealth Management* (20:1), pp. 30–36.

Faul, F., Erdfelder, E., Lang, A.-G., and Buchner, A. 2007. "G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences," *Behavior Research Methods* (39:2), pp. 175–191.

Flavián, C., Guinalíu, M., and Torres, E. 2005. "The influence of corporate image on consumer trust," *Internet Research* (15:4), pp. 447–470.

Fornell, C., and Larcker, D. F. 1981. "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research* (18:1), p. 39-50.

Forsythe, S. M., and Shi, B. 2003. "Consumer patronage and risk perceptions in Internet shopping," *Journal of Business Research* (56:11), pp. 867–875.

Gefen, D., Karahanna, E., and Straub, D. W. 2003. "Trust and TAM in Online Shopping: An Integrated Model," *MIS Quarterly* (27:1), pp. 51-90.

Glaser, F., Iliewa, Z., Jung, D., and Weber, M. 2019. "Towards Designing Robo-advisors for Unexperienced Investors with Experience Sampling of Time-Series Data," in *Information Systems and Neuroscience: NeuroIS Retreat 2018*, F. D. Davis, R. Riedl, J. vom Brocke, P.-M. Léger and A. B. Randolph (eds.), Cham: Springer International Publishing, pp. 133–138.

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)*, Los Angeles, London, New Delhi, Singapore, Washington DC, Melbourne: Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. 2019. "When to use and how to report the results of PLS-SEM," *European Business Review* (31:1), pp. 2–24.

Heinrich, P., and Schwabe, G. (2018). "Facilitating informed decision-making in financial service encounters," *Business & Information Systems Engineering* (60:4), pp. 317–329.

Jarvenpaa, S. L., Tractinsky, N., and Vitale, M. 2000. "Consumer trust in an Internet store," *Information Technology and Management* (1), pp. 45–71.

Jung, D., Dorner, V., Weinhardt, C., and Pusmaz, H. 2018a. "Designing a robo-advisor for risk-averse, low-budget consumers," *Electronic Markets* (28:3), pp. 367–380.

Jung, D., Erdfelde, E., and Glaser, F. 2018b. "Nudged to Win: Designing Robo-Advisory to Overcome Decision Inertia," in *Proceedings of the 26th European Conference on Information Systems (ECIS 2018). Research-in-Progress Papers*. 19.

Ji, M. 2017. "Are robots good fiduciaries? Regulating robo-advisors under the investment advisers act of 1940," *Columbia Law Review* (117:6), pp. 1543–1583.

Kesharwani, A., and Singh Bisht, S. 2012. "The impact of trust and perceived risk on internet banking adoption in India," *International Journal of Bank Marketing* (30:4), pp. 303–322.

Kilic, M., Heinrich, P., and Schwabe, G. 2015. "Coercing into Completeness in Financial Advisory Service Encounters," in *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, D. Cosley, A. Forte, L. Ciolfi and D. McDonald (eds.), Vancouver, BC, Canada. pp. 283–311.

Kim, K. K., and Prabhakar, B. 2004. "Initial trust and the adoption of B2C e-commerce," *ACM SIGMIS Database* (35:2), pp. 50–64.

Kim, G., Shin, B., and Lee, H. G. 2009. "Understanding dynamics between initial trust and usage intentions of mobile banking," *Information Systems Journal* (19:3), pp. 283–311.

Kundu, S., and Datta, S. K. 2015. "Impact of trust on the relationship of e-service quality and customer satisfaction," *EuroMed Journal of Business* (10:1), pp. 21–46.

Lee, S., Choi, J., Ngo-Ye, T. L., and Cummings, M. 2018. "Modeling Trust in the Adoption Decision Process of Robo-Advisors: An Agent-Based Simulation Approach," in *MWAIS 2018 Proceedings. 24*.

Lee, K. C., Kang, I., and McKnight, D. H. 2007. "Transfer From Offline Trust to Key Online Perceptions: An Empirical Study," *IEEE Transactions on Engineering Management* (54:4), pp. 729–741.

Luo, X., Li, H., Zhang, J., and Shim, J. P. 2010. "Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services," *Decision Support Systems* (49:2), pp. 222–234.

Malaquias, R. F., and Hwang, Y. 2016. "An empirical study on trust in mobile banking: A developing country perspective," *Computers in Human Behavior* (54), pp. 453–461.

Malhotra, N. K., Kim, S. S., and Agarwal, J. 2004. "Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model," *Information Systems Research* (15:4), pp. 336–355.

McKnight, D. H., Choudhury, V., and Kacmar, C. 2002. "The impact of initial consumer trust on intentions to transact with a web site: a trust building model," *Journal of Strategic Information Systems* (11:3–4), pp. 297–323.

McKnight, D. H., Cummings, L. L., and Chervany, N. L. 1998. "Initial Trust Formation in New Organizational Relationships," *Academy of Management Review* (23:3), pp. 473–490.

McKnight, D. H., Carter, M., Thatcher, J. B., and Clay, P. F. 2011. "Trust in a specific technology: An investigation of its components and measures," *ACM Transactions on Management Information Systems (TMIS)* (2:2), pp. 1–25.

McQuarrie, A. D. R., and Tsai, C.-L. 1998. *Regression and Time Series Model Selection,* Singapore, New Jersey, London, Hong Kong*:* World Scientific.

Moin, S. M. A., Devlin, J., and McKechnie, S. 2015. "Trust in financial services: Impact of institutional trust and dispositional trust on trusting belief," *Journal of Financial Services Marketing* (20:2), pp. 91-106.

Pavlou, P. A., and Gefen, D. 2004. "Building effective online marketplaces with institution-based trust," *Information Systems Research* (15:1), pp. 37–59.

Phoon, K., and Koh, F. 2017. "Robo-Advisors and Wealth Management," *The Journal of Alternative Investments* (20:3), pp. 79–94.

Rühr, A., Berger, B., and Hess, T. 2019. "Can I Control My Robo-Advisor? Trade-Offs in Automation and User Control in (Digital) Investment Management," in *Proceedings of the 25th Americas Conference on Information Systems (AMCIS 2019)*, forthcoming.

Ruf, C., Back, A., Bergmann, R., and Schlegel, M. 2015. "Elicitation of Requirements for the Design of Mobile Financial Advisory Services -- Instantiation and Validation of the Requirement Data Model with a Multi-method Approach," in *2015 48th Hawaii International Conference on System Sciences,* HI, USA, pp. 1169–1178.

Roca, J. C., García, J. J., and de la Vega, J. J. 2009. "The importance of perceived trust, security and privacy in online trading systems," *Information Management & Computer Security* (17:2), pp. 96–113.

Schwarz, G. 1978. "Estimating the Dimension of a Model," *The Annals of Statistics* (6:2), pp. 461–464.

Sharma, P. N., Shmueli, G., Sarstedt, M., Danks, N., and Ray, S. 2018. "Prediction-Oriented Model Selection in Partial Least Squares Path Modeling," *Decision Sciences*, forthcoming.

Statista 2019. *Robo-Advisors*: *worldwide.* (https://www.statista.com/outlook/337/100/robo-advisors/worldwide, accessed 18 April 2019).

Suh, B., and Han, I. 2002. "Effect of trust on customer acceptance of Internet banking," *Electronic Commerce Research and Applications* (1:3-4), pp. 247–263.

Venkatesh, V., Morris, M. G., and Davis, G. B. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425–478.

Yap, K. B., Wong, D. H., Loh, C., and Bak, R. 2010. "Offline and online banking – where to draw the line when building trust in e-banking?," *International Journal of Bank Marketing* (28:1), pp. 27–46.

Zhou, T. 2012. "Understanding users' initial trust in mobile banking: An elaboration likelihood perspective," *Computers in Human Behavior* (28:4), pp. 1518–1525.