



HAL
open science

Acceptance of digital investment solutions: The case of robo advisory in Germany

Volker Seiler, Katharina Maria Fanenbruck

► **To cite this version:**

Volker Seiler, Katharina Maria Fanenbruck. Acceptance of digital investment solutions: The case of robo advisory in Germany. *Research in International Business and Finance*, 2021, 58, pp.101490. 10.1016/j.ribaf.2021.101490 . hal-04079211

HAL Id: hal-04079211

<https://hal.science/hal-04079211v1>

Submitted on 22 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Acceptance of Digital Investment Solutions: The Case of Robo Advisory in Germany

Volker Seiler¹ and Katharina Maria Fanenbruck²

ABSTRACT

The financial services sector is undergoing substantial change due to technological innovation and digitalization. Traditional banks face intensifying competition through the market entry of digital investment platforms that make use of automated investment advisory, so-called robo advisors. Based on replica of two German robo advisors, a sample of 96 participants assessed their intention to use such digital investment services. The results obtained using partial least squares (PLS) path modelling indicate that perceived usefulness and privacy are the most decisive factors with a one percent higher perceived usefulness (higher privacy) increasing usage intentions by 0.57% (0.25%). The results are robust to various socio-demographic and FinTech-related controls as well as alternative estimation procedures such as generalized structured component analysis (GSCA).

JEL Classification: D14, G23, G41, O14, O16, O39

Keywords: FinTech, Robo Advisory, Technology Acceptance, Disruption, Partial Least Squares (PLS), Generalized Structured Component Analysis (GSCA)

¹ Corresponding author: Associate Professor in Finance, EM Normandie, Métis Lab, Campus de Caen, 9 Rue Claude Bloch, 14052 Caen Cedex4, France, Phone: +33 231-46-2860, Email: VSeiler@em-normandie.fr.

² Ernst & Young GmbH Wirtschaftsprüfungsgesellschaft, Arnulfstr. 59, 80636 Munich, Germany, Phone: +49 85-14331-22407, Email: Katharina.Fanenbruck@parthenon.ey.com.

Acknowledgements: We are grateful to John W. Goodell (Editor) and an anonymous reviewer for their many helpful comments. We thank the two FinTechs that agreed to participate in this project and the organizers of the Vietnam Symposium in Banking and Finance 2020 for helpful comments and suggestions. Any remaining errors are our own. Katharina Maria Fanenbruck gratefully acknowledges financial support provided by GFFT Gemeinnützige Gesellschaft zur Förderung des Forschungstransfers e.V. This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors. Declaration of interest: None.

Acceptance of Digital Investment Solutions: The Case of Robo Advisory in Germany

ABSTRACT

The financial services sector is undergoing substantial change due to technological innovation and digitalization. Traditional banks face intensifying competition through the market entry of digital investment platforms that make use of automated investment advisory, so-called robo advisors. Based on replica of two German robo advisors, a sample of 96 participants assessed their intention to use such digital investment services. The results obtained using partial least squares (PLS) path modelling indicate that perceived usefulness and privacy are the most decisive factors with a one percent higher perceived usefulness (higher privacy) increasing usage intentions by 0.57% (0.25%). The results are robust to various socio-demographic and FinTech-related controls as well as alternative estimation procedures such as generalized structured component analysis (GSCA).

JEL Classification: D14, G23, G41, O14, O16, O39

Keywords: FinTech, Robo Advisory, Technology Acceptance, Disruption, Partial Least Squares (PLS), Generalized Structured Component Analysis (GSCA)

1. Introduction

The traditional banking sector is currently facing intensifying competition through the market entry of technology-based start-ups, so-called FinTechs, which cover various areas such as banking, asset & wealth management, lending, crowdfunding, insurance, trading, and handling of payments (see for example the overviews in Sironi, 2016, Dorfleitner et al., 2017, Gomber et al., 2017, Gomber et al., 2018, and Thakor, 2020). While many traditional banks struggle with innovations because their infrastructures are entrenched and the mindset of the organization is oftentimes not focused on innovation, FinTechs have the advantage that they are closer to their customers and can start from scratch, as they have no legacy. Moreover, FinTechs are often not burdened with regulatory requirements as banks are; they offer specialized products and services and often do not even possess a banking licence. On the other hand, FinTechs usually are rather young companies that are not yet established in the market and do not have a well-known brand. Hence, they frequently lack a sound customer base as well as trust, which is a precondition when it comes to financial services (Jünger and Mietzner, 2020).

One of the under-researched areas in the field of digital finance and FinTechs identified by Gomber et al. (2017) and Lucey et al. (2018) are asset allocation solutions, i.e., robo advisory. Robo advisors use algorithms and asset allocation models to provide investment advice as well as discretionary investment management services. They are less costly than other options of investment advisory and give private investors the opportunity to invest in various asset classes even if they do not possess deep knowledge about finance and investments (Gomber et al., 2018). Based on a set of questions regarding risk appetite, liquidity preferences, prior experience with financial instruments, investment horizon and demographics, robo advisors recommend an investment strategy. Depending on the extent of automatization, they also provide automatic rebalancing and shift funds between different asset classes. This is facilitated by using artificial intelligence and big data applications such as machine learning (see for example Belanche et al., 2019, D'Hondt et al., 2020, Shanmuganathan, 2020, and Tao et al., 2021).

Given this background, the key question is how potential users evaluate these applications for online investment and what impacts their decision to use them in the first place. Academic literature on the subject is scarce, however. Jünger and Mietzner (2020) recently addressed the question what drives customers to switch from traditional retail banking service providers to FinTechs. However, given the broad range of services provided under the umbrella term FinTech, this label might have different meanings to different people. Moreover, FinTechs usually focus

on one particular service offering rather than being a full-service provider. Thus, the analysis of Jünger and Mietzner (2020) adopts a rather generic setting and does not allow to derive specific managerial implications. Besides, customers might be willing to use FinTechs for some applications while relying on their bank for others. Hence, the focus on switching, i.e., exclusive reliance on FinTechs, limits the scope of the analysis: It remains unclear, what factors drive usage intentions of FinTechs in general. The paper that comes closest to ours is Belanche et al. (2019). In their thought experiment, participants are told to imagine having used a robo advisor. Given that investment decision making in general and the usage of robo advisory in particular is an abstract task, it is questionable whether the instructions given by Belanche et al. (2019) allow users to clearly picture what a robo advisor does look like and what kind of services it may perform; the usage of a thought experiment rather than having participants exposed to a robo advisor obviously presents a major shortcoming which is aggravated by the fact that detailed information about the investment principles and algorithm of the robo advisor increase the likelihood of investors to delegate financial decision making to digital investment platforms (Litterscheidt and Streich, 2020). To summarize, the question which determinants drive the acceptance and usage intentions of digital investment platforms is poorly understood and under-examined.

In order to address this gap, our study adds to the scant literature on the adoption of FinTech services such as robo advisory in the following ways: First, we examine the main determinants of acceptance of digital investment platforms to shed further light on the drivers of usage adoption. Second, we propose a novel way to make an abstract service such as robo advisory more tangible: In order to give participants a better understanding of the capabilities of robo advisors, we employ replica of two German digital asset management solution platforms having the same appearance and offering the same information as the original FinTechs but without their brand names and logos so as to ensure anonymity. Participants had the chance to navigate the robo advisor replica and make themselves familiar with its functionality before completing an online questionnaire on their usage intentions and different drivers thereof. Finally, the findings are of managerial relevance and might be used to improve the service offering of robo advisors to better address customers' needs. Accordingly, our paper is not only of interest to academics in the field but relevant for practitioners alike.

The results point to perceived usefulness and perceived privacy being the most important drivers of the intention to use a robo advisor while content (i.e., the kind of information provided) and design (i.e., the visualization) have no significant impact. Moreover, usage intentions are

lower for females, while participants who use online banking or have previous experience with investment funds show higher usage intentions. Whether a robo advisor has a well-known brand or a banking licence does not have a significant effect on usage intentions. Likewise, subjects do not show higher usage intentions for those robo advisors that are a division of a traditional bank. The results are robust to alternative model specifications and different estimation techniques.

The remainder of this paper is structured as follows: Section 2 presents an overview of the growing body of literature on robo advisory. Section 3 provides the theoretical framework, our data gathering process and the methodology used for our analyses, while Section 4 presents the empirical results of our study. Section 5 concludes.

2. Related Literature

While academic literature on FinTechs and robo advisory is scarce, it is evolving at a fast pace. Sironi (2016), Dorfleitner et al. (2017), Gomber et al. (2017), Gomber et al. (2018) and Thakor (2020) provide overviews that help to navigate the growing number of publications and to better understand the different business models and services. More specific research on robo advisors connected to our paper is provided by Belanche et al. (2019), Jünger and Mietzner (2020), Bhatia et al. (2020), Brenner and Meyll (2020), D'Hondt et al. (2020), Hildebrand and Bergner (2020), Litterscheidt and Streich (2020), Shanmuganathan (2020), Bai (2021) and Tao et al. (2021).

A first strand of literature focuses on customer acceptance of digital investment management platforms. Belanche et al. (2019) is one of the earliest papers to study the adoption of robo advisory. For their analysis, they use a web survey of 765 participants from the U.S., UK and Portugal. Subjects were provided with some general information on robo advisors and the instruction to imagine having some amount of money for investment and being offered the opportunity to use a robo advisor before answering the items of the different constructs of the model and some socio-demographic questions (age, gender, familiarity with robo advisory). Rather than focusing on usage intentions and adoption of robo advisory as such, Jünger and Mietzner (2020) address the question what drives customers to switch from traditional retail banking service providers to FinTechs. Their findings show that financial expertise, preferences for transparency and trust are key drivers of switching decisions. Brenner and Meyll (2020) document a substantial negative relationship between robo advisory usage and the need to seek human financial advice for a sample of 2,000 U.S. investors. This finding is especially strong for investors concerned

about conflicts of interest of human financial advisors¹ that might negatively affect the quality of financial advice and ultimately result in outright investment fraud. Thus, Brenner and Meyll (2020) conclude that especially investors who distrust human financial advisors are more prone to rely on robo advisory. Moreover, users of digital investment platforms tend to be less financially literate, younger, and among the lower income brackets. These findings are replicated for a sample of 1,762 U.S. investors by Bai (2021). Hildebrand and Bergner (2020) shed further light on the question how robo advisors can establish trust by contrasting non-conversational and conversational robo advisors.² Their findings reveal that the latter are able to increase the level of trust towards the digital investment platform which in turn affects investor behaviour and perception of the financial services firm: Not only are conversational robo advisors able to increase the likelihood of compliance with the investment recommendations; customers also believe that the financial services firm acts in their best interest. Moreover, the increase in affective trust leads to a reallocation of assets towards conversational robo advisors.

A second strand of literature grounded in behavioural finance evolves around the idea that robo advisors might have the potential to mitigate behavioural biases of investors, thus leading to better investment decisions. To this end, Bhatia et al. (2020) surveyed 34 Indian experts from the banking and financial services industry as well as non-bank financial institutions, FinTechs and the IT sector. The structured content analysis of the interviews shows that the current focus of robo advisors is to educate investors and build trust, thereby increasing the awareness level and acceptance of digital investment platforms. Currently, capabilities concerning risk analysis, customer segmentation and mitigation of behavioural biases seem to be limited, though. Quantitative evidence concerning the mitigation of behavioural biases is provided by D'Acunto et al. (2019) who compare the portfolios of Indian adopters of robo advisory and non-adopters. Their results indicate that users of robo advisors achieve diversification benefits which holds true for both, undiversified and already well-diversified portfolios, with the effects being larger for the former. More precisely, adopters of robo advisory are less affected by disposition, trend following and rank effects. In a similar vein, Tao et al. (2021) show that robo advisors by far achieve a superior risk adjusted performance compared to pure equity, fixed income and money market funds as well as hybrid funds over the period 2016-2019. Furthermore, robo advisors outperform both, mutual funds as well as equity indices. Using artificial intelligence (AI) robo advisor alter egos

¹ For extensive studies of financial advisory and conflicts of interest see Bolton et al. (2007), Danilov et al. (2013) and Burke et al. (2015).

² We thank one anonymous reviewer for drawing our attention to this literature.

that match a sample of 22,972 Belgian retail investors, D'Hondt et al. (2020) are able to show that especially investors with lower incomes and lower levels of education benefit from robo advisory. Moreover, portfolios built by the AI alter egos substantially outperformed those of retail investors during the financial crisis of 2008.

3. Model, Data and Methodology

3.1 Proposed Model

Following Belanche et al. (2019), we use the technology acceptance model (TAM) of Davis (1989) which models user intentions to adopt a new technology as a result of that technology's perceived usefulness and perceived ease of use as the theoretical framework for our analysis. TAM is flexible and usually extended by additional constructs in order to adjust the model to the specific context (see Legris et al., 2003, for an overview). Borrowing from the e-commerce literature, we consider perceived risk to be an important determinant of the intention to use digital investment solutions. Riskiness of using robo advisors is not understood as the riskiness of the investment as such as measured by volatility, maximum drawdown, value at risk, expected shortfall or some other risk measure; in the context of digital investment platforms perceived risk rather refers to the uncertainty users are facing with respect to the digital investment management platform itself: Transactions may fail or users might suffer a monetary loss due to malfunctions (see Pavlou, 2003, and Wu and Wang, 2005).

Another concern arising from performing monetary transactions online is privacy. During financial transactions, sensitive data is transferred from one point to another and is therefore vulnerable to information leakage. Examining customer choice of different channels for financial services, Black et al. (2002) show that people are especially reluctant to disclose personal or confidential financial information using the internet. This is further underlined by Poon (2008) who finds privacy and security to be the main determinants of user adoption of e-banking services. Likewise, Susanto et al. (2016) find perceived security and privacy to be significant predictors when it comes to the decision whether to continue usage of smartphone banking services. It is intuitive that customers are more likely to use an investment platform if they consider their data and assets to be handled safely and with confidentiality.

In addition to the two e-commerce specific variables, we consider content, design, and assessment of risk preferences as platform specific variables. Pikkarainen et al. (2004) and Poon (2007) show that informative content is an important determinant of customer usage of online

banking services. Investment decision making is an activity which requires solid information. On the one hand, there is information that is legally required to be provided to customers. On the other hand, customers voluntarily seek additional information. In a traditional brick-and-mortar banking setting, customers usually prefer face-to-face interactions with a trustworthy financial advisor (Black et al., 2002). However, direct face-to-face interaction is at odds with the idea of robo advisory and automated asset allocation. Hence, the lack of personal interaction needs to be compensated for by providing all the content customers need for their decision making.³

Besides providing the content itself, we expect the way in which the content is presented to influence usage intentions. Design refers to the appearance of the application, i.e. the user interface (Shanmuganathan, 2020), and helps to structure the content and make it easier to comprehend. If the design is appealing, customers are more inclined to spend time on the website and perceive it to be more credible. In the context of online banking, Poon (2008) refers to design as attractiveness of screen layouts, graphics, and colour configurations. The design aspect is especially important in the context of robo advisory, as FinTechs in general focus on innovative designs of their user interfaces as a major selling proposition (Shanmuganathan, 2020).

Before customers are able to use any digital investment management solution, they are required to go through an onboarding process where several questions with regards to their willingness to take losses are being asked (see for example Tertilt and Scholz, 2018). The aim is to elicit their risk aversion. Hence, we are interested in examining the degree to which the robo advisor is able to assess a customer's risk aversion and propose an investment strategy that reflects these risk preferences: When the recommended investment strategy contains more risk than customers are willing to tolerate, they might be worried about their savings and feel uneasy so that the intention to use robo advisory will be less likely. Likewise, if customers are willing to take higher risks in order to achieve a higher return, they will be disappointed if the recommended strategy contains less risk and hence falls short of their return expectations. The second case is even more precarious as in the context of robo advisors customers usually can self-select a strategy that contains less risk than recommended but are not able to choose upwards. In fact, Tertilt and Scholz (2018) show that some questions asked when assessing an investor's risk profile do not seem to influence the risk categorization at all and that the equity exposure recommended by robo advisors generally tends to be conservative, thus reducing the expected return.

³ The usage of so-called "conversational" robo advisors using chatbots (see Hildebrand and Berger, 2020) might provide an alternative.

Moreover, we control for both, socio-demographic (gender, age, whether the subject is a student or not, highest academic degree, financial literacy, monthly assets, experience with online deposits and experience with investment funds) and FinTech-specific (having a well-known brand, having a banking licence and being the division of a bank) variables.

Please note that we are not able to assess actual usage; thus, our key dependent variable is the intention to use digital investment platforms. Figure 1 summarizes our model: Perceived ease of use and perceived usefulness are the key constructs we borrow from the technology acceptance model, perceived risk and perceived privacy are e-commerce specific determinants, whereas content, design and assessment of risk preferences are platform specific determinants.

– Please insert Figure 1 about here –

3.2 Data Collection and Sample Composition

We collected data between 13 and 28 February 2018 making use of two German FinTechs offering robo advisory and operating since three to four years to empirically analyze the proposed model. In order to assure anonymity, we built replica of the respective websites but removed all labels, names and logos. We then randomly assigned participants to one of the two platforms. Participants first went through the onboarding process, since the recommended investment strategies depend on the answers given to questions concerning risk preferences, investment horizon and liquidity needs in this stage. Next, participants were able to navigate the platform and familiarize themselves with the different functionalities. Subsequently, the determinants for technology acceptance as well as socio-demographic characteristics were surveyed. Screenshots from the robo advisor replica are presented in Appendix A while the specific items included in the questionnaire and a description of the variables are available in Appendix B.

In total, we obtained 96 usable observations, consisting of 37 (38.54%) female and 59 (61.46%) male participants. The average age of the participants is 28.68 years, ranging from 19 to 69 years, which is in line with the age of respondents reported in the analysis of Jünger and Mietzner (2020). 48 respondents (50.00%) have experience with online securities deposits while only 34 participants (35.42%) have experience with investment funds. Given that according to the Deutsche Bundesbank's most recent "Panel on Household Finances (PHF)" only 16% of German households own mutual funds (Deutsche Bundesbank, 2019), this number seems reasonable. The low percentage of investment fund ownership reflects the fact that German households prefer

liquid investments over mutual funds and direct share investments. With regards to monthly liquid funds available after deduction of all regular costs, participants could group themselves into different brackets. 48 participants (50.00%) reported monthly assets below EUR 399. This number is driven by 58 respondents (60.42%) being students. As digital asset management solutions are appealing to young investors with low account balances and limited personal wealth (Polyak, 2015, Dorfleitner et al., 2017, and Bain, 2019), our sample seems representative for the target group of robo advisors. Table 1 summarizes the composition of our sample.

– Please insert Table 1 about here –

3.3 Methodology

We use partial least squares (PLS) path modelling⁴ to analyze our model of technology acceptance of digital investment platforms. While it is possible to use alternatives such as principal component regression (see Jünger and Mietzner, 2020), PLS is better suited if the purpose of the analysis is to predict some endogenous variable rather than testing theory and offers the advantage of being able to work with small samples and data that is not normally distributed (Jöreskog and Wold, 1982, Lohmöller, 1989, and Chin, 1998).⁵ More precisely, the minimum sample size should be equal to the larger of ten times the largest number of path coefficients directed toward an endogenous construct (largest structural equation) or ten times the largest number of formative items, in case the model includes formative constructs (largest measurement equation) (Chin, 1998, and Hair et al., 2011). With a maximum of 7 exogenous constructs pointing towards usage intention in our baseline model (see Figure 1), our sample meets this criterion.

PLS recently gained increasing acceptance in banking and finance research with applications including construction of sentiment indices (Huang et al., 2015, and Xu and Zhou, 2018), the assessment of the impact of macroeconomic variables on exchange rate volatility (Adusei and Gyapong, 2017), prediction of financial distress (Mselmi et al., 2017), transmission of systemic risk and stress testing (Avkiran et al., 2018), and the analysis of credit relationships between savings banks and small and medium-sized enterprises (SMEs) (Hirsch et al., 2018).⁶

⁴ All estimations are run using SmartPLS 3 (Ringle et al., 2015).

⁵ Please note that Hadi and Ling (1998) explicitly caution against the use of principal component regression.

⁶ For further examples see the edited volume by Avkiran and Ringle (2018).

4. Results

4.1 Reliability and Validity Assessment of Measurement Models

We model the latent constructs using reflective indicators for the measurement models. Except for items PEASE02, DESIGN01, DESIGN02, DESIGN03 and PERPRIV04, the minimum indicator reliability threshold of 0.50 required by Fornell and Larcker (1981) is met, as the indicator loadings are ≥ 0.70 (see Table 2). Internal consistency is given for all scales, as the values for Cronbach's α (Cronbach, 1951, and Cortina, 1993) and Jöreskog's ρ (Jöreskog, 1971, Werts et al., 1974, and Fornell and Larcker, 1981) exceed 0.70. Please note that the loadings of PEASE02 and PERPRIV04 are statistically significant at the 10% and 1% level, respectively. Furthermore, both items possess small predictive relevance as to Stone-Geisser's Q^2 (Geisser, 1974, 1975, and Stone, 1974). Accordingly, we decided to not remove the two items from the analysis.⁷ To summarize, with the exception of the measurement model for *DESIGN*, internal consistency, composite reliability and predictive validity are given.

– Please insert Table 2 about here –

We next look at convergent validity, i.e., the consistency of items measuring a latent construct, and discriminant validity in order to assess construct validity (Cronbach and Meehl, 1955, and Peter, 1981). With the exception of *DESIGN*, the average variance extracted (AVE) for all constructs exceeds the minimum threshold of 0.50 (Fornell and Larcker, 1981, and Chin, 1998) so that convergent validity is given. Likewise, all construct correlations are lower than the square root of the AVE (see Table 3, Panel A), so that discriminant validity is given as to the Fornell-Larcker criterion (Fornell and Larcker, 1981). This is further supported by the heterotrait-monotrait (HTMT) criterion proposed by Henseler et al. (2015), as the heterotrait-monotrait ratios of correlations are well below 0.90 (see Table 3, Panel B). In summary, construct validity seems acceptable.

– Please insert Table 3 about here –

⁷ Dropping PEASE02 and PERPRIV04 does neither change the reliability nor the validity of the scale. Likewise, exclusion of these items does neither change the magnitude nor the significance of the path coefficients of the structural model.

4.2. Assessment of Structural Model

4.2.1 Main Results

Table 4 presents the estimates of both, direct and total effects, for the baseline model as depicted in Figure 1, as well as alternative model specifications when removing insignificant paths. The baseline specification in column (1) shows that the explained variance for usage intention (*INTUSE*), our main variable of interest, as judged by the R^2 of 0.454 is moderate (Chin, 1998). Moreover, Stone-Geisser's Q^2 (Geisser, 1974, 1975, and Stone, 1974) of 0.320 shows that the model has medium predictive validity. With regards to the explanatory variables, the intention to use robo advisory is mainly driven by perceived usefulness (*PUSE*) and perceived privacy (*PERPRIV*) which both have a positive impact; the effect size as judged by the f^2 value is moderate (weak) for *PUSE* (*PERPRIV*).

It is interesting to note that perceived ease of use (*PEASE*) as one of the core variables of the technology acceptance model has no significant effect on usage intentions. This might be explained by the fact that perceived usefulness fully mediates the effect of perceived ease of use on usage intention (see Zhao et al., 2010, and Nitzl et al., 2016): The mean of the indirect effect which we get from multiplying the path coefficients from *PEASE* to *PUSE* and from *PUSE* to *INTUSE* over all 5,000 Bootstrap samples is 0.316 with a standard error of 0.087 which yields a pseudo t -value of 3.630 indicating statistical significance at the 1% level. Likewise, the 95% Bootstrap confidence interval (two-sided test) for the indirect effect (MacKinnon et al., 2004, and Wood, 2005) has a lower (upper) bound of 0.166 (0.504) so that 0 is not included.

The three platform-specific variables *CONTENT*, *DESIGN* and *RISKASSESS* do not have a significant effect on usage intentions. As the measurement models of *CONTENT* and *RISKASSESS* meet the reliability and validity criteria usually used to assess the scales (see Tables 2 and 3), the two variables do not seem to be primary drivers of the intention to use robo advisory. However, please note that the scale for *DESIGN* does not pass the reliability and validity assessment. Removing either *CONTENT* (model (2)) or *CONTENT* and *DESIGN* simultaneously (model (3)) does not change the results with regards to our main variable of interest, *INTUSE*. For the e-commerce specific variables we find a positive effect of perceived privacy (*PERPRIV*) on usage intention which is significant at the 10% level while we find a negative but insignificant effect of perceived risk (*PERRISK*). As in this case the indirect effect is insignificant and the 95% Bootstrap confidence interval includes 0, this finding cannot be attributed to mediation.

– Please insert Table 4 about here –

4.2.2 Impact of Socio-Demographic and FinTech Controls

In order to assess the robustness of our results, we add socio-demographic controls and re-estimate our baseline model. The results presented in Table 5 show that controlling for socio-demographic variables does not change our main findings: The intention to use robo advisory is mainly driven by the perceived usefulness and perceived privacy of such a service. Interestingly and in contrast to Belanche et al. (2019), women have a lower usage intention than men as indicated by the strong negative path coefficient of -0.315 for *SEX* that is statistically significant at the 1% level. If adoption of robo advisory is perceived to be risky, this result is in line with general findings that women are more risk averse than men (see for example Brooks et al., 2019). Furthermore, respondents that have experience with using online deposits (*ONLDEP*) or investment funds (*INVFUND*) have significantly higher usage intentions. Please note that when both control variables are added simultaneously the two effects cannot be isolated so that the impact of *INVFUND* on *INTUSE* is no longer significant. However, unlike Jünger and Mietzner (2020), we do not find financial literacy to have any influence on usage intentions: The path coefficient of 0.029 for *FINLIT* is neither of economic nor of statistical significance.

– Please insert Table 5 about here –

As a second robustness check, we control for FinTech characteristics. More precisely, we re-estimate our baseline model when adding variables that assess whether respondents would be more willing to make use of the digital investment platform when the robo advisor has a well-known brand (*BRAND*), the robo advisor has a banking licence (*LICENCE*) or when the platform is a division of a traditional bank (*BANKDIV*). Again, our main result that *INTUSE* is mainly driven by perceived usefulness and perceived privacy does not change. Moreover, none of the three FinTech controls has a significant effect on usage intentions (see Table 6); when added simultaneously, we find that *BRAND* has a negative effect on *INTUSE*. However, some caveat seems appropriate, as the negative path coefficient of -0.187 is statistically significant at the 10% level only.

– Please insert Table 6 about here –

4.2.3 Usage of Generalized Structural Component Analysis

As a last robustness check, we follow Avkiran (2018) and Avkiran et al. (2018) and re-estimate our model using generalized structured component analysis (GSCA)⁸ introduced by Hwang and Takane (2004, 2014). The choice of generalized structured component analysis is driven by both, PLS and GSCA being variance-based methods, latent variables being modelled as components rather than factors and the main application being prediction rather than theory testing.

The detailed results are presented in Appendix D. With regards to overall model assessment, PLS and GSCA both provide a coefficient of determination of the same magnitude for *INTUSE*, our main variable of interest (R_{PLS}^2 : 0.454; R_{GSCA}^2 : 0.453), and *PERRISK* (R_{PLS}^2 : 0.140; R_{GSCA}^2 : 0.141). Only for *PUSE* do we find a slightly lower coefficient of determination when using GSCA for the estimation (R_{PLS}^2 : 0.290; R_{GSCA}^2 : 0.232). Likewise, there are no fundamental differences with regards to size and significance of the path coefficients with the exception of perceived privacy: Although of a similar magnitude, the direct effect of *PERPRIV* on *INTUSE* is no longer statistically significant (t -value of 1.557). Similarly, the assessment of the measurement models does not reveal any profound differences. In summary, the re-estimation using generalized structured component analysis strengthens the robustness of the results obtained by partial least squares.

5. Conclusion

This paper analyses the usage intentions of digital investment platforms and complements previous research by Belanche et al. (2019) and Jünger and Mietzner (2020) thus contributing to the scarce literature on robo advisor adoption. Using an extended version of the technology acceptance model (Davis, 1989), we investigate which factors increase usage intentions. In order to give participants a better understanding of the capabilities of digital investment platforms and make their abstract services more tangible, we propose the usage of replica of two robo advisors.

The results suggest that perceived ease of use and privacy are the two main drivers of usage intentions with the former being particularly important, as the overall impact is more than twice as large (0.584 vs. 0.269). Moreover, we find that usage intentions of females are significantly lower (by about 23%-32%, depending on whether all socio-demographic controls are included or *SEX* is the only socio-demographic control), which is somewhat lower than the 43% of

⁸ The estimation is run using web gesca 1.5 (Hwang et al., 2019).

female robo advisory users documented by Brenner and Meyll (2020) but in line with D'Acunto et al. (2019) who find that 71% of robo advisor adopters in their sample are male. Although not statistically significant, the negative conditional effects of *AGE*, *FINLIT* and *ASSETSLOW* when including all socio-demographic controls simultaneously corroborate previous results of Brenner and Meyll (2020) that users of digital investment platforms tend to be younger, less financially literate and among the lower income brackets. The finding that customers do not differentiate between robo advisors with and without banking licence or those being a division of a bank might seem puzzling only at first sight: While checking accounts are protected up to EUR 100,000 as to the German deposit insurance scheme in case a bank goes bankrupt, this coverage does not extend to securities custody accounts so that there is a level playing fields with regards of ownership of a banking licence. Moreover, the erosion of trust during the financial crisis (see Burke and Hung, 2015, and van der Crujisen et al., 2016) might play to the advantage of FinTechs rather than banks, which supports the finding of Brenner and Meyll (2020) that investors who distrust human financial advisors are more prone to rely on robo advisory.

Besides addressing a gap in the academic literature, our results bear the following managerial implications: When trying to attract customers to their digital investment management platforms, providers of robo advisory should clearly emphasize the usefulness and privacy of their service offerings, as these two factors are the main drivers of usage adoption. Moreover, when it comes to customer segmentation, females are more reluctant to use robo advisory, which might be due to women caring less about financial investment or being more risk averse than men (see Brooks et al., 2019, for a recent example). Accordingly, special initiatives targeted at women are needed if the aim is to tap into this underserved customer group and attract more female users to digital investment platforms. Furthermore, while not being able to benefit from having a banking licence or a strong brand, traditional banks adding robo advisory to their service portfolio might be able to transfer their online banking customers and those having prior experience with investment funds to their digital asset management platforms. In light of customer acquisition costs between 300 and 1,000 USD per new customer (Wong, 2015), we hope that our findings provide some useful information for managerial decisions in the digital asset management industry. Given that investors who use robo advisory are able to better diversify their portfolios thus achieving higher returns and less volatility (D'Acunto et al., 2019) and the strong growth of this FinTech segment with estimates of the assets under management ranging from 3 billion to 600 billion EUR for Germany in 2035 (Dorfleitner et al., 2017), more studies are needed in order to assess

the robustness of our findings. Moreover, the majority of research on FinTechs and robo advisors focuses on single country studies. Thus, international studies across countries might help to foster our understanding of the cultural differences and determinants important to users when it comes to acceptance of digital asset management solutions. We leave this for future research.

References

- Adusei, M. and Gyapong, E.Y. (2017): The impact of macroeconomic variables on exchange rate volatility in Ghana: The partial least squares structural equation modelling approach, in: *Research in International Business and Finance*, Vol. 42, 1428-1444, <https://doi.org/10.1016/j.ribaf.2017.07.081>
- Avkiran, N.K. (2018): Rise of the partial least squares structural equation modeling: An application in banking, in: Avkiran, N.K. and Ringle, C.M. (Eds.): *Partial least squares structural equation modeling. Recent advances in banking and finance*, International Series in Operations Research & Management Science, Vol. 267, Springer International Publishing, Cham, 1-29, https://doi.org/10.1007/978-3-319-71691-6_1
- Avkiran, N.K. and Ringle, C.M. (2018): *Partial least squares structural equation modeling. Recent advances in banking and finance*, International Series in Operations Research & Management Science, Vol. 267, Springer International Publishing, Cham, <https://doi.org/10.1007/978-3-319-71691-6>
- Avkiran, N.K., Ringle, C.M. and Low, R. (2018): Monitoring transmission of systemic risk: Application of partial least squares structural equation modeling in financial stress testing, in: *Journal of Risk*, Vol. 20 (5), 83-115, 10.21314/JOR.2018.386
- Bhatia, A., Chandani, A. and Chhateja, J. (2020): Robo advisory and its potential in addressing the behavioural biases of investors – A qualitative study in Indian context, in: *Journal of Behavioral and Experimental Finance*, Vol. 25, *forthcoming*, <https://doi.org/10.1016/j.jbef.2020.100281>
- Bai, Z. (2021): Does robo-advisory help reduce the likelihood of carrying a credit card debt? Evidence from an instrumental variable approach, in: *Journal of Behavioral and Experimental Finance*, Vol. 29, *forthcoming*, <https://doi.org/10.1016/j.jbef.2021.100461>
- Bain, I. (2019): Where millennials turn for financial advice, *Financial Times*, 15 March 2019, <https://www.ft.com/content/1390be10-4404-11e9-b83b-0c525dad548f>
- Belanche, D., Casaló, L.V. and Flavián, C. (2019): Artificial intelligences in FinTech: Understanding robo-advisors adoption among customers, in: *Industrial Management & Data Systems*, Vol. 119 (7), 1411-1430, <https://doi.org/10.1108/IMDS-08-2018-0368>
- Black, N.J., Lockett, A., Ennew, C., Winklhofer, H. and McKechnie, S. (2002): Modelling consumer choice of distribution channels: An illustration from financial services, in: *International Journal of Bank Marketing*, Vol. 20 (4), 161-173, <https://doi.org/10.1108/02652320210432945>
- Bolton, P., Freixas, X. and Shapiro, J. (2007): Conflicts of interest, information provision, and competition in the financial services industry, in: *Journal of Financial Economics*, Vol. 85 (2), 297-330, <https://doi.org/10.1016/j.jfineco.2005.06.004>
- Brenner, L. and Meyll, T. (2020): Robo-advisors: A substitute for human financial advice? In: *Journal of Behavioral and Experimental Finance*, Vol. 25, *forthcoming*, <https://doi.org/10.1016/j.jbef.2020.100275>

- Brooks, C., Sangiorgi, I., Hillenbrand, C. and Money, K. (2019): Experience wears the trousers: Exploring gender and attitude to financial risk, in: *Journal of Economic Behavior & Organization*, Vol. 163, 483-515, <https://doi.org/10.1016/j.jebo.2019.04.026>
- Burke, J. and Hung, A.A. (2015): Trust and financial advice, RAND Working Paper Series WR-1075, <https://doi.org/10.7249/WR1075>
- Burke, J., Hung, A.A., Clift, J., Garber, S. and Yoong, J.K. (2015): Impacts of conflicts of interest in the financial services industry, RAND Working Paper Series WR-1076, <https://doi.org/10.7249/WR1076>
- Chin, W.W. (1998): The partial least squares approach to structural equation modeling, in: Maroulides, G.A. (Ed.): *Modern Methods for Business Research*, Lawrence Erlbaum Associates, Mahwah, 295-336
- Cortina, J.M. (1993): What is coefficient alpha? An examination of theory and applications, in: *Journal of Applied Psychology*, Vol. 78 (1), 98-104, <https://doi.org/10.1037/0021-9010.78.1.98>
- Cronbach, L.J. (1951): Coefficient alpha and the internal structure of tests, in: *Psychometrika*, Vol. 16, 297-334, <https://doi.org/10.1007/BF02310555>
- Cronbach, L.J. and Meehl, P.E. (1955): Construct validity in psychological tests, in: *Psychological Bulletin*, Vol. 52 (4), 281-302, <https://doi.org/10.1037/h0040957>
- D'Acunto, F., Prabhala, N. and Rossi, A.G. (2019): The promises and pitfalls of robo-advising, in: *Review of Financial Studies*, Vol. 32 (5), 1983-2020, <https://doi.org/10.1093/rfs/hhz014>
- D'Hondt, C., De Winne, R., Ghysels, E. and Raymond, S. (2020): Artificial intelligence alter egos: Who might benefit from robo-investing? In: *Journal of Empirical Finance*, Vol. 59, 248-299, <https://doi.org/10.1016/j.jempfin.2020.10.002>
- Danilov, A., Biemann, T., Kring, T. and Sliwka, D. (2013): The dark side of team incentives: Experimental evidence on advice quality from financial service professionals, in: *Journal of Economic Behavior & Organization*, Vol. 93, 266-272, <https://doi.org/10.1016/j.jebo.2013.03.012>
- Davis, F.D. (1989): Perceived usefulness, perceived ease of use, and user acceptance of information technology, in: *MIS Quarterly*, Vol. 13 (3), 319-340, <https://doi.org/10.2307/249008>
- Deutsche Bundesbank (2019): *Monthly Report*, Vol. 71 (4), April 2019
- Dorfleitner, G., Hornuf, L., Schmitt, M. and Weber, M. (2017): *FinTech in Germany*, Springer International Publishing, Cham, <https://doi.org/10.1007/978-3-319-54666-7>
- Efron, B. (1979): Bootstrap methods: Another look at the Jackknife, in: *The Annals of Statistics*, Vol. 7 (1), 1-26, <https://www.jstor.org/stable/2958830>

Fornell, C. and Larcker, D.F. (1981): Evaluating structural equation models with unobservable variables and measurement error, in: *Journal of Marketing Research*, Vol. 18 (1), 39-50, <https://doi.org/10.2307/3151312>

Geisser, S. (1974): A predictive approach to the random effect model, in: *Biometrika*, Vol. 61 (1), 101-107, <https://doi.org/10.1093/biomet/61.1.101>

Geisser, S. (1975): The predictive sample reuse method with applications, in: *Journal of the American Statistical Association*, Vol. 70 (350), 320-328, <https://doi.org/10.2307/2285815>

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W. (2018): On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services, in: *Journal of Management Information Systems*, Vol. 35 (1), 220-265, <https://doi.org/10.1080/07421222.2018.1440766>

Gomber, P., Koch, J.-A. and Siering, M. (2017): Digital finance and FinTech: Current research and future research directions, in: *Journal of Business Economics*, Vol. 87 (5), 537-580, <https://doi.org/10.1007/s11573-017-0852-x>

Hadi, A.S. and Ling, R.F. (1998): Some cautionary notes on the use of principal components regression, in: *The American Statistician*, Vol. 52 (1), 15-19, <https://doi.org/10.1080/00031305.1998.10480530>

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011): PLS-SEM: Indeed a silver bullet, in: *Journal of Marketing Theory and Practice*, Vol. 19 (2), 139-151, <https://doi.org/10.2753/MTP1069-6679190202>

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015): A new criterion for assessing discriminant validity in variance-based structural equation modeling, in: *Journal of the Academy of Marketing Science*, Vol. 43, 115-135, <https://doi.org/10.1007/s11747-014-0403-8>

Hildebrand, C. and Bergner, A. (2020): Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making, in: *Journal of the Academy of Marketing Science*, *forthcoming*, <https://doi.org/10.1007/s11747-020-00753-z>

Hirsch, B, Nitzl, C. and Schoen, M. (2018): Interorganizational trust and agency costs in credit relationships between savings banks and SMEs, in: *Journal of Banking and Finance*, Vol. 97, 37-50, <https://doi.org/10.1016/j.jbankfin.2018.09.017>

Huang, D., Jiang, F., Tu, J. and Zhou, G. (2015): Investor sentiment aligned: A powerful predictor of stock returns, in: *The Review of Financial Studies*, Vol. 28 (3), 791-837, <https://doi.org/10.1093/rfs/hhu080>

Hwang, H., Jung, K. and Kim, S. (2019): Web GESCA (Version 1.5), available from <http://sem-gesca.com/webgesca>

Hwang, H. and Takane, Y. (2004): Generalized structured component analysis, in: *Psychometrika*, Vol. 69 (1), 81-99, <https://doi.org/10.1007/BF02295841>

Hwang, H. and Takane, Y. (2014): Generalized structured component analysis: A component-based approach to structural equation modeling, Chapman and Hall/CRC, Boca Raton/London/New York, <https://doi.org/10.1201/b17872>

Jöreskog, K.G. (1971): Statistical analysis of sets of congeneric tests, in: *Psychometrika*, Vol. 36, 109-133, <https://doi.org/10.1007/BF02291393>

Jöreskog, K.G. and Wold, H. (1982): The ML and PLS techniques for modeling with latent variables. Historical and comparative aspects, in: Jöreskog, K.G and Wold, H. (Eds.): *Systems under indirect observation. Causality – structure – prediction*, Vol. 1, North-Holland Publishing Company, Amsterdam/New York/Oxford, 263-270

Jünger, M. and Mietzner, M. (2020): Banking goes digital: The adoption of FinTech services by German households, in: *Finance Research Letters*, Vol. 34, *forthcoming*, <https://doi.org/10.1016/j.frl.2019.08.008>

Legris, P., Ingham, J. and Collette, P. (2003): Why do people use information technology? A critical review of the technology acceptance model, in: *Information & Management*, Vol. 40 (3), 191-204, [https://doi.org/10.1016/S0378-7206\(01\)00143-4](https://doi.org/10.1016/S0378-7206(01)00143-4)

Litterscheidt, R. and Streich, D.J. (2020): Financial education and digital asset management: What's in the black box? In: *Journal of Behavioral and Experimental Economics*, Vol. 87, *forthcoming*, <https://doi.org/10.1016/j.socec.2020.101573>

Lohmöller, J.-B. (1989): Latent variable path modelling with partial least squares, Physica-Verlag, Heidelberg, <https://doi.org/10.1007/978-3-642-52512-4>

Lucey, B.M., Vigne, S.A., Ballester, L., Barbopoulos, L., Brzezczynski, J., Carchano, O., Dimic, N., Fernandez, V., Gogolin, F., González-Urteaga, A., Goodwell, J.W., Helbing, P., Ichev, R., Kearney, F., Laing, E., Larkin, C.J., Lindblad, A., Lončarski, I., Ly, K.C., Marinč, M., McGee, R.J., McGroarty, F., Neville, C., O'Hagan-Luff, M., Piljak, V., Sevic, A., Sheng, X., Stafylas, D., Urquhart, A., Versteeg, R., Vu, A.N., Wolfe, S., Yarovaya, L. and Zaghini, A. (2018): Future directions in international financial integration research – A crowdsourced perspective, in: *International Review of Financial Analysis*, Vol. 55, 35-49, <https://doi.org/10.1016/j.irfa.2017.10.008>

MacKinnon, D.P., Lockwood, C.M. and Williams, J. (2004): Confidence limits for the indirect effect: Distribution of the product and resampling methods, in: *Multivariate Behavioral Research*, Vol. 39 (1), 99-128, https://doi.org/10.1207/s15327906mbr3901_4

Mselmi, N., Lahiani, A. and Hamza, T. (2017): Financial distress prediction: The case of French small and medium-sized firms, in: *International Review of Financial Analysis*, Vol. 50, 67-80, <https://doi.org/10.1016/j.irfa.2017.02.004>

Nitzl, C., Roldan, J.L. and Cepeda, G. (2016): Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models, in: *Industrial Management & Data Systems*, Vol. 116 (9), 1849-1864, <https://doi.org/10.1108/IMDS-07-2015-0302>

Pavlou, P.A. (2003): Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model, in: *International Journal of Electronic Commerce*, Vol. 7 (3), 101-134, <https://doi.org/10.1080/10864415.2003.11044275>

Peter, P.J. (1981): Construct validity: A review of basic issues and marketing practices, in: *Journal of Marketing Research*, Vol. 18 (2), 133-145, <https://doi.org/10.2307/3150948>

Pikkarainen, T., Pikkarainen, K., Karjaluoto, H. and Pahnla, S. (2004): Consumer acceptance of online banking: An extension of the technology acceptance model, in: *Internet Research*, Vol. 14 (3), 224-235, <https://doi.org/10.1108/10662240410542652>

Polyak, I. (2015): Millennials and robo-advisors: A match made in heaven?, CNBC, 22 June 2015, <https://www.cnbc.com/2015/06/21/millennials-and-robo-advisors-a-match-made-in-heaven.html>

Poon, W.-C. (2008): Users' adoption of e-banking services: The Malaysian perspective, in: *Journal of Business & Industrial Marketing*, Vol. 23 (1), 59-69, <https://doi.org/10.1108/08858620810841498>

Ringle, C.M., Wende, S. and Becker, J.-M. (2015): *SmartPLS 3*. Boenningstedt: SmartPLS GmbH, <http://www.smartpls.com>

Shanmuganathan, M. (2020): Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions, in: *Journal of Behavioral and Experimental Finance*, Vol. 27, *forthcoming*, <https://doi.org/10.1016/j.jbef.2020.100297>

Sironi, P. (2016): *FinTech innovation: From Robo-Advisors to goal based investing and gamification*, John Wiley & Sons, Chichester

Stone, M. (1974): Cross-validated choice and assessment of statistical predictions, in: *Journal of the Royal Statistical Society: Series B (Methodological)*, Vol. 36 (2), 111-133, <https://doi.org/10.1111/j.2517-6161.1974.tb00994.x>

Susanto, A., Chang, Y. and Ha, Y. (2016): Determinants of continuance intention to use the smartphone banking services. An extension to the expectation-confirmation model, in: *Industrial Management & Data Systems*, Vol. 116 (3), 508-525, <https://doi.org/10.1108/IMDS-05-2015-0195>

Tao, R., Su, C.-W., Xiao, Y., Dai, K. and Khalid, F. (2021): Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets, in: *Technological Forecasting & Social Change*, Vol. 163, *forthcoming*, <https://doi.org/10.1016/j.techfore.2020.120421>

Tertilt, M. and Scholz, P. (2018): To advise, or not to advise – How robo-advisors evaluate the risk preferences of private investors, in: *Journal of Wealth Management*, Vol. 21 (2), 70-84, <https://doi.org/10.3905/jwm.2018.21.2.070>

Thakor, A.V. (2020): Fintech and banking: What do we know? In: Journal of Financial Intermediation, Vol. 41, *forthcoming*, <https://doi.org/10.1016/j.jfi.2019.100833>

Van der Crujisen, C., de Haan, J. and Jansen, D.-J. (2016): Trust and financial crisis experiences, in: Social Indicators Research, Vol. 127, 577-600, <https://doi.org/10.1007/s11205-015-0984-8>

Werts, C.E., Linn, R.L. and Jöreskog, K.G. (1974): Intraclass reliability estimates: Testing structural assumptions, in: Educational and Psychological Measurement, Vol. 34 (1), 26-33, <https://doi.org/10.1177/001316447403400104>

Wong, M.M. (2015): Hungry robo-advisors are eyeing wealth management assets. We believe wealth management moats can repel the fiber-clad legion, Morningstar, Chicago

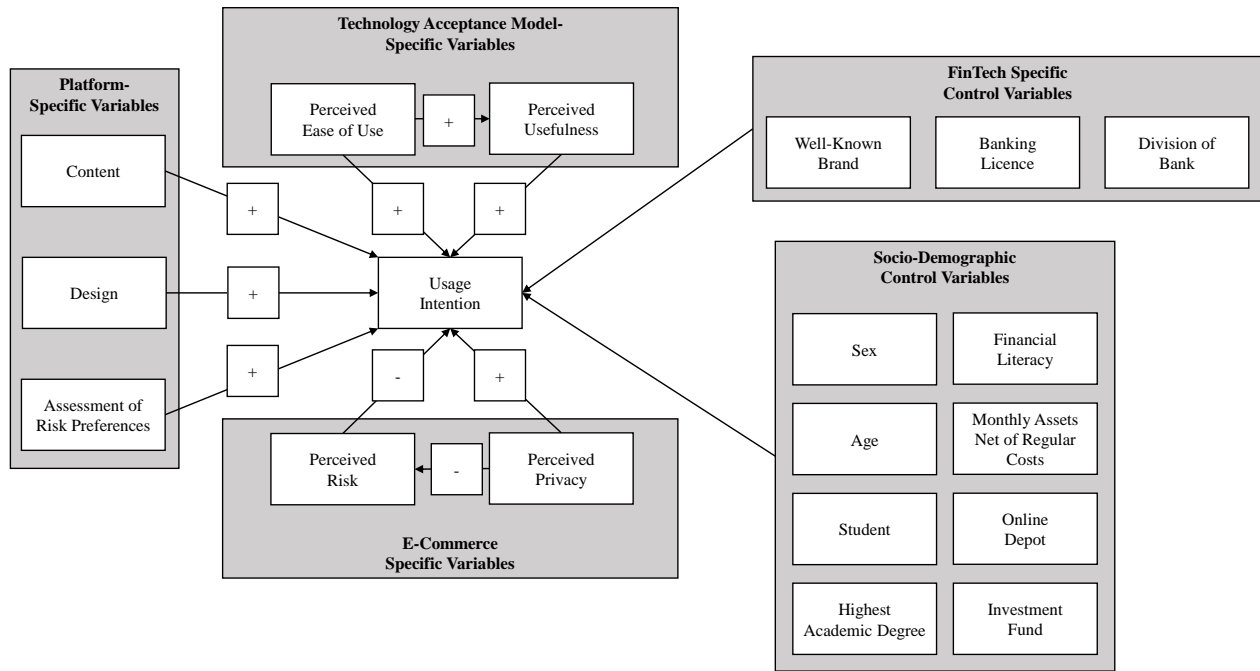
Wood, M. (2005): Bootstrapped confidence intervals as an approach to statistical inference, in: Organizational Research Methods, Vol. 8 (4), 454-470, <https://doi.org/10.1177/1094428105280059>

Wu, J.-H. and Wang, S.-C. (2005): What drives mobile commerce? An empirical evaluation of the revised technology acceptance model, in: Information & Management, Vol. 42 (5), 719-729, <https://doi.org/10.1016/j.im.2004.07.001>

Xu, H.-C. and Zhou, W.-X. (2018): A weekly sentiment index and the cross-section of stock returns, in: Finance Research Letters, Vol. 27, 135-139, <https://doi.org/10.1016/j.frl.2018.02.009>

Zhao, X., Lynch, J.G. Jr. and Chen, Q. (2010): Reconsidering Baron and Kenny: Myths and Truths about mediation analysis, in: Journal of Consumer Research, Vol. 37 (2), 197-206, <https://doi.org/10.1086/651257>

Figure 1: Proposed Model



This Figure presents the proposed model framework for the analysis.

Table 1: Composition of Sample

	N	%
<i>Panel A: Sex</i>		
Female	37	38.54
Male	59	61.46
<i>Panel B: Online Securities Depot</i>		
Experience	48	50.00
No Experience	48	50.00
<i>Panel C: Investment Funds</i>		
Experience	34	35.42
No Experience	62	64.58
<i>Panel D: Occupation</i>		
Student	58	60.42
Employee	29	30.21
Self-employed	5	5.21
Civil servant	3	3.13
Other	1	1.04
<i>Panel E: Highest Academic Degree</i>		
No degree	24	25.00
Bachelor	37	38.54
Master/Diplom	29	30.21
Other	6	6.25
<i>Panel F: Monthly Assets</i>		
< EUR 100	2	2.08
EUR 100 - EUR 199	13	13.54
EUR 200 - EUR 299	12	12.50
EUR 300 - EUR 399	21	21.88
EUR 400 - EUR 499	6	6.25
EUR 500 - EUR 999	19	19.79
> EUR 1,000	23	23.96

This table presents the composition of the sample as to socio-demographic indicators. Monthly assets refers to monthly liquid funds after deduction of all regular costs.

Table 2: Assessment of Measurement Models – Internal Consistency, Composite Reliability, Convergent Validity and Predictive Validity

Construct	Item	Loading	<i>t</i> -Value	Indicator Reliability	Cronbach's α	Jöreskog's ρ	AVE	Stone-Geisser Q^2
<i>INTUSE</i>	INTUSE01	0.920***	47.909	0.846	0.863	0.916	0.785	0.592+++
	INTUSE02	0.842***	19.227	0.709				0.473+++
	INTUSE03	0.894***	34.277	0.799				0.564+++
<i>PEASE</i>	PEASE01	0.936***	23.924	0.876	0.806	0.853	0.612	0.471+++
	PEASE02	0.389*	1.951	0.151				0.111+
	PEASE03	0.773***	7.369	0.598				0.398+++
	PEASE04	0.907***	12.891	0.823				0.628+++
<i>PUSE</i>	PUSE01	0.936***	51.673	0.876	0.918	0.948	0.860	0.693+++
	PUSE02	0.918***	37.016	0.843				0.660+++
	PUSE03	0.928***	52.944	0.861				0.661+++
<i>CONTENT</i>	CONT01	0.888***	3.153	0.789	0.853	0.906	0.765	0.479+++
	CONT02	0.946***	3.672	0.895				0.472+++
	CONT03	0.782**	2.547	0.612				0.410+++
<i>DESIGN</i>	DESIGN01	0.310	0.666	0.096	0.773	0.568	0.310	-0.184
	DESIGN02	0.289	0.602	0.084				0.155+
	DESIGN03	0.328	0.759	0.108				-0.048
	DESIGN04	0.977**	2.072	0.955				-0.044
<i>RISKASSESS</i>	RISKASSESS01	0.931***	5.874	0.867	0.854	0.907	0.767	0.575+++
	RISKASSESS02	0.939***	5.644	0.882				0.662+++
	RISKASSESS03	0.744***	2.934	0.554				0.359+++
<i>PERPRIV</i>	PERPRIV01	0.876***	18.250	0.767	0.741	0.855	0.668	0.492+++
	PERPRIV02	0.922***	40.526	0.850				0.510+++
	PERPRIV03	0.622***	4.914	0.387				0.102+
<i>PERRISK</i>	PERRISK01	0.839***	15.908	0.704	0.891	0.924	0.752	0.488+++
	PERRISK02	0.906***	31.753	0.821				0.594+++
	PERRISK03	0.851***	15.786	0.724				0.590+++
	PERRISK04	0.871***	19.019	0.759				0.593+++

This table presents the assessment of the measurement models as to their internal consistency, composite reliability, convergent validity and predictive relevance. Bootstrapped *t*-values (2-sided test) based on 5,000 Bootstrap samples (Efron, 1979). AVE: Average variance extracted. ***/**/* indicates statistical significance at the 1%/5%/10% level. +++/++/+ indicates high/medium/small predictive relevance. *INTUSE*: Usage intention. *PEASE*: Perceived ease of use. *PUSE*: Perceived usefulness. *CONTENT*: Content provided by the robo advisor. *DESIGN*: Design of the user interface of the robo advisor. *RISKASSESS*: Risk assessment. *PERPRIV*: Perceived privacy. *PERRISK*: Perceived risk.

Table 3: Assessment of Measurement Models – Discriminant Validity

	<i>INTUSE</i>	<i>PEASE</i>	<i>PUSE</i>	<i>CONTENT</i>	<i>DESIGN</i>	<i>RISKASSESS</i>	<i>PERPRIV</i>	<i>PERRISK</i>
<i>Panel A: Fornell-Larcker Criterion</i>								
<i>INTUSE</i>	0.886							
<i>PEASE</i>	0.232	0.782						
<i>PUSE</i>	0.620	0.539	0.927					
<i>CONTENT</i>	0.122	0.562	0.279	0.874				
<i>DESIGN</i>	0.136	0.352	0.335	0.419	0.557			
<i>RISKASSESS</i>	0.191	0.318	0.290	0.541	0.256	0.876		
<i>PERPRIV</i>	0.497	0.318	0.509	0.259	0.297	0.313	0.817	
<i>PERRISK</i>	-0.305	-0.058	-0.345	-0.043	-0.029	-0.110	-0.374	0.867
<i>Panel B: Heterotrait-Monotrait Ratio</i>								
<i>INTUSE</i>								
<i>PEASE</i>	0.241							
<i>PUSE</i>	0.688	0.485						
<i>CONTENT</i>	0.151	0.732	0.310					
<i>DESIGN</i>	0.157	0.729	0.270	0.833				
<i>RISKASSESS</i>	0.218	0.432	0.333	0.677	0.674			
<i>PERPRIV</i>	0.609	0.369	0.587	0.323	0.379	0.396		
<i>PERRISK</i>	0.326	0.085	0.374	0.075	0.083	0.143	0.447	

This table presents the Fornell-Larcker criterion (Fornell and Larcker, 1981) in Panel A and the heterotrait-monotrait ratio (Henseler et al., 2015) in Panel B. In Panel A, the square root of the average variance extracted (AVE) is displayed in the main diagonal in bold print and the construct correlations are presented underneath. *INTUSE*: Usage intention. *PEASE*: Perceived ease of use. *PUSE*: Perceived usefulness. *CONTENT*: Content provided by the robo advisor. *DESIGN*: Design of the user interface of the robo advisor. *RISKASSESS*: Risk assessment. *PERPRIV*: Perceived privacy. *PERRISK*: Perceived risk.

Table 4: Baseline Model and Alternative Specifications

	Direct Effects			Total Effects		
	(1)	(2)	(3)	(1)	(2)	(3)
Endogenous Variable: Usage Intention						
<i>PEASE</i>	-0.138 (0.996) [0.018]	-0.142 (1.111) [0.019]	-0.154 (1.402) [0.028]+	0.176 (1.141)	0.164 (1.126)	0.153 (1.196)
<i>PUSE</i>	0.584 (4.211)*** [0.326]++	0.567 (4.535)*** [0.313]++	0.570 (4.441)*** [0.320]++	0.584 (4.211)***	0.567 (4.535)***	0.570 (4.441)***
<i>CONTENT</i>	0.006 (0.048) [0.000]	-0.025 (0.198) [0.001]		0.006 (0.048)	-0.025 (0.198)	
<i>DESIGN</i>	-0.093 (0.760) [0.012]			-0.093 (0.760)		
<i>RISKASSESS</i>	0.002 (0.020) [0.000]	0.003 (0.029) [0.000]	-0.007 (0.070) [0.000]	0.002 (0.020)	0.003 (0.029)	-0.007 (0.070)
<i>PERPRIV</i>	0.263 (1.682)* [0.083]+	0.249 (1.597) [0.075]+	0.248 (1.556) [0.074]+	0.269 (1.857)*	0.258 (1.800)*	0.258 (1.746)*
<i>PERRISK</i>	-0.015 (0.152) [0.000]	-0.026 (0.262) [0.001]	-0.026 (0.263) [0.001]	-0.015 (0.152)	-0.026 (0.262)	-0.026 (0.263)
<i>N</i>	96	96	96			
<i>R</i> ²	0.454	0.448	0.448			
<i>R</i> _{adj.} ²	0.410	0.411	0.417			
<i>Q</i> ²	0.320++	0.318++	0.322++			
Endogenous Variable: Perceived Usefulness						
<i>PEASE</i>	0.539 (6.284)*** [0.409]+++	0.539 (6.010)*** [0.410]+++	0.539 (6.628)*** [0.410]+++			
<i>R</i> ²	0.290	0.291	0.291			
<i>R</i> _{adj.} ²	0.283	0.283	0.283			
<i>Q</i> ²	0.235++	0.236++	0.236++			
Endogenous Variable: Perceived Risk						
<i>PERPRIV</i>	-0.374 (3.775)*** [0.162]++	-0.374 (3.813)*** [0.162]++	-0.374 (3.832)*** [0.162]++			
<i>R</i> ²	0.140	0.140	0.140			
<i>R</i> _{adj.} ²	0.131	0.130	0.131			
<i>Q</i> ²	0.088+	0.088+	0.088+			

This table presents the results of the baseline model as presented in Figure 1 as well as alternative specifications when removing insignificant paths. Bootstrapped *t*-values (2-sided test) based on 5,000 Bootstrap samples in parentheses (Efron, 1979). Effect size *f*² in squared brackets. *N*: Number of observations. *Q*²: Stone-Geisser measure of predictive relevance (Geisser, 1974, 1975, and Stone, 1974); omission distance *D*=7. Highest variance inflation factor for Model (1): *CONTENT*: 2.027; highest variance inflation factor for Model (2): *PEASE*: 1.977; highest variance inflation factor for Model (3): *PUSE*: 1.841. ***/**/* indicates statistical significance at the 1%/5%/10% level. +++/++/+ indicates high/medium/small effect size (*f*²) and high/medium/small predictive relevance (*Q*²), respectively. *PEASE*: Perceived ease of use. *PUSE*: Perceived usefulness. *CONTENT*: Content provided by the robo advisor. *DESIGN*: Design of the user interface of the robo advisor. *RISKASSESS*: Risk assessment. *PERPRIV*: Perceived privacy. *PERRISK*: Perceived risk.

Table 5: Baseline Model and Socio-Demographic Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Endogenous Variable: Usage Intention										
<i>PEASE</i>	-0.208 (1.455) [0.047]+	-0.146 (1.034) [0.019]	-0.150 (1.098) [0.021]+	-0.139 (0.994) [0.017]	-0.143 (1.032) [0.019]	-0.142 (1.022) [0.019]	-0.157 (1.254) [0.027]+	-0.125 (0.925) [0.015]	-0.141 (1.023) [0.019]	-0.181 (1.296) [0.036]+
<i>PUSE</i>	0.574 (4.731)*** [0.373]+++	0.592 (4.115)*** [0.321]++	0.594 (4.240)*** [0.338]++	0.585 (4.045)*** [0.316]++	0.582 (4.190)*** [0.322]++	0.578 (4.017)*** [0.312]++	0.546 (4.292)*** [0.332]++	0.619 (4.696)*** [0.378]+++	0.581 (4.162)*** [0.326]++	0.518 (3.464)*** [0.270]++
<i>CONTENT</i>	0.026 (0.199) [0.001]	0.012 (0.095) [0.000]	0.015 (0.120) [0.000]	0.006 (0.050) [0.000]	0.007 (0.052) [0.000]	0.006 (0.049) [0.000]	0.053 (0.451) [0.003]	-0.010 (0.083) [0.000]	-0.001 (0.011) [0.000]	0.038 (0.277) [0.002]
<i>DESIGN</i>	-0.006 (0.050) [0.000]	-0.090 (0.744) [0.011]	-0.091 (0.733) [0.012]	-0.093 (0.766) [0.012]	-0.093 (0.749) [0.012]	-0.090 (0.723) [0.011]	-0.033 (0.264) [0.002]	-0.069 (0.590) [0.007]	-0.093 (0.754) [0.012]	-0.001 (0.008) [0.000]
<i>RISKASSESS</i>	0.020 (0.192) [0.001]	-0.004 (0.035) [0.000]	-0.005 (0.041) [0.000]	0.002 (0.020) [0.000]	0.010 (0.085) [0.000]	0.006 (0.047) [0.000]	0.016 (0.160) [0.000]	0.021 (0.186) [0.001]	0.007 (0.057) [0.000]	0.045 (0.389) [0.003]
<i>PERPRIV</i>	0.325 (2.251)** [0.145]+	0.256 (1.555) [0.075]+	0.257 (1.594) [0.079]+	0.264 (1.682)* [0.082]+	0.261 (1.664)* [0.081]+	0.263 (1.681)* [0.082]+	0.223 (1.610) [0.068]+	0.240 (1.568) [0.072]+	0.252 (1.559) [0.076]+	0.280 (1.988)** [0.108]+
<i>PERRISK</i>	-0.007 (0.082) [0.000]	-0.018 (0.187) [0.000]	-0.001 (0.008) [0.000]	-0.015 (0.153) [0.000]	-0.009 (0.091) [0.000]	-0.019 (0.189) [0.000]	-0.034 (0.383) [0.002]	-0.022 (0.225) [0.001]	-0.018 (0.178) [0.000]	-0.009 (0.098) [0.000]

(continued)

Table 5: Baseline Model and Socio-Demographic Controls – Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Socio-Demographic Controls										
<i>SEX</i>	-0.315 (3.684)*** [0.186]++									-0.234 (2.255)** [0.093]+
<i>AGE</i>		0.029 (0.371) [0.001]								-0.074 (0.748) [0.007]
<i>STUDENT</i>			-0.080 (1.055) [0.011]							-0.037 (0.278) [0.001]
<i>BACHELOR</i>				-0.002 (0.027) [0.000]						0.054 (0.580) [0.004]
<i>MASTER /DIPL</i>					0.041 (0.548) [0.003]					0.039 (0.308) [0.002]
<i>FINLIT</i>						0.029 (0.317) [0.001]				-0.031 (0.333) [0.002]
<i>ONLDEP</i>							0.294 (4.038)*** [0.169]++			0.230 (2.023)** [0.065]+
<i>INVFUND</i>								0.177 (2.339)** [0.055]+		-0.010 (0.090) [0.000]
<i>ASSETSLOW</i>									-0.094 (1.156) [0.016]	-0.077 (0.815) [0.008]
<i>N</i>	96	96	96	96	96	96	96	96	96	96
<i>R</i> ²	0.540	0.455	0.460	0.454	0.456	0.455	0.532	0.483	0.462	0.585
<i>R</i> _{adj.} ²	0.498	0.404	0.411	0.404	0.406	0.405	0.489	0.435	0.413	0.501
<i>Q</i> ²	0.383+++	0.319++	0.323++	0.316++	0.318++	0.315++	0.378+++	0.339++	0.322++	0.389+++

(continued)

Table 5: Baseline Model and Socio-Demographic Controls – Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Endogenous Variable: Perceived Usefulness										
<i>PEASE</i>	0.539 (6.383)*** [0.409]+++	0.539 (6.416)*** [0.409]+++	0.539 (5.984)*** [0.410]+++	0.539 (5.634)*** [0.409]+++	0.539 (5.963)*** [0.410]+++	0.539 (6.353)*** [0.409]+++	0.538 (6.453)*** [0.408]+++	0.539 (6.345)*** [0.409]+++	0.539 (6.665)*** [0.409]+++	0.539 (6.301)*** [0.409]+++
R^2	0.290	0.290	0.291	0.290	0.291	0.290	0.290	0.290	0.291	0.290
$R^2_{adj.}$	0.283	0.283	0.283	0.283	0.283	0.283	0.282	0.283	0.283	0.283
Q^2	0.235++	0.236++	0.236++	0.235++	0.236++	0.236++	0.235++	0.235++	0.236++	0.235++
Endogenous Variable: Perceived Risk										
<i>PERPRIV</i>	-0.374 (3.803)*** [0.162]++	-0.374 (3.848)*** [0.162]++	-0.374 (3.836)*** [0.162]++	-0.374 (3.882)*** [0.162]++	-0.374 (3.820)*** [0.162]++	-0.374 (3.934)*** [0.162]++	-0.374 (3.862)*** [0.162]++	-0.374 (3.840)*** [0.162]++	-0.374 (3.847)*** [0.162]++	-0.374 (3.850)*** [0.162]++
R^2	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140	0.140
$R^2_{adj.}$	0.131	0.131	0.130	0.131	0.130	0.131	0.131	0.131	0.130	0.131
Q^2	0.088+	0.088+	0.088+	0.088+	0.088+	0.088+	0.088+	0.088+	0.088+	0.088+

This table presents the results of the baseline model as presented in Figure 1 adding socio-demographic controls. Bootstrapped t -values (2-sided test) based on 5,000 Bootstrap samples in parentheses (Efron, 1979). Effect size f^2 in squared brackets. N : Number of observations. Q^2 : Stone-Geisser measure of predictive relevance (Geisser, 1974, 1975, and Stone, 1974); omission distance $D=7$. Variance inflation factors are reported in Table C.1 in the Appendix. ***/**/* indicates statistical significance at the 1%/5%/10% level. +++/++/+ indicates high/medium/small effect size (f^2) and high/medium/small predictive relevance (Q^2), respectively. *PEASE*: Perceived ease of use. *PUSE*: Perceived usefulness. *CONTENT*: Content provided by the robo advisor. *DESIGN*: Design of the user interface of the robo advisor. *RISKASSESS*: Risk assessment. *PERPRIV*: Perceived privacy. *PERRISK*: Perceived risk. *SEX*: Dummy variable that is 1 if the respondent is female and 0 otherwise. *AGE*: Age of the respondent in years. *STUDENT*: Dummy variable that is 1 if the respondent is a student and 0 otherwise. *BACHELOR*: Dummy variable that is 1 if the highest academic degree of the respondent is a Bachelor degree and 0 otherwise. *MASTER/DIPL*: Dummy variable that is 1 if the highest academic degree of the respondent is either a Master degree or a Diplom and 0 otherwise. *FINLIT*: Financial literacy (see Table B.2 in the Appendix for further details). *ONLDEP*: Dummy variable that is 1 if the respondent has previous experience with online securities deposits and 0 otherwise. *INVFUND*: Dummy variable that is 1 if the respondent has previous experience with investment funds and 0 otherwise. *ASSETSLOW*: Dummy variable that is 1 if monthly liquid funds after deduction of all regular costs of the respondent are below EUR 399.

Table 6: Baseline Model and FinTech Controls

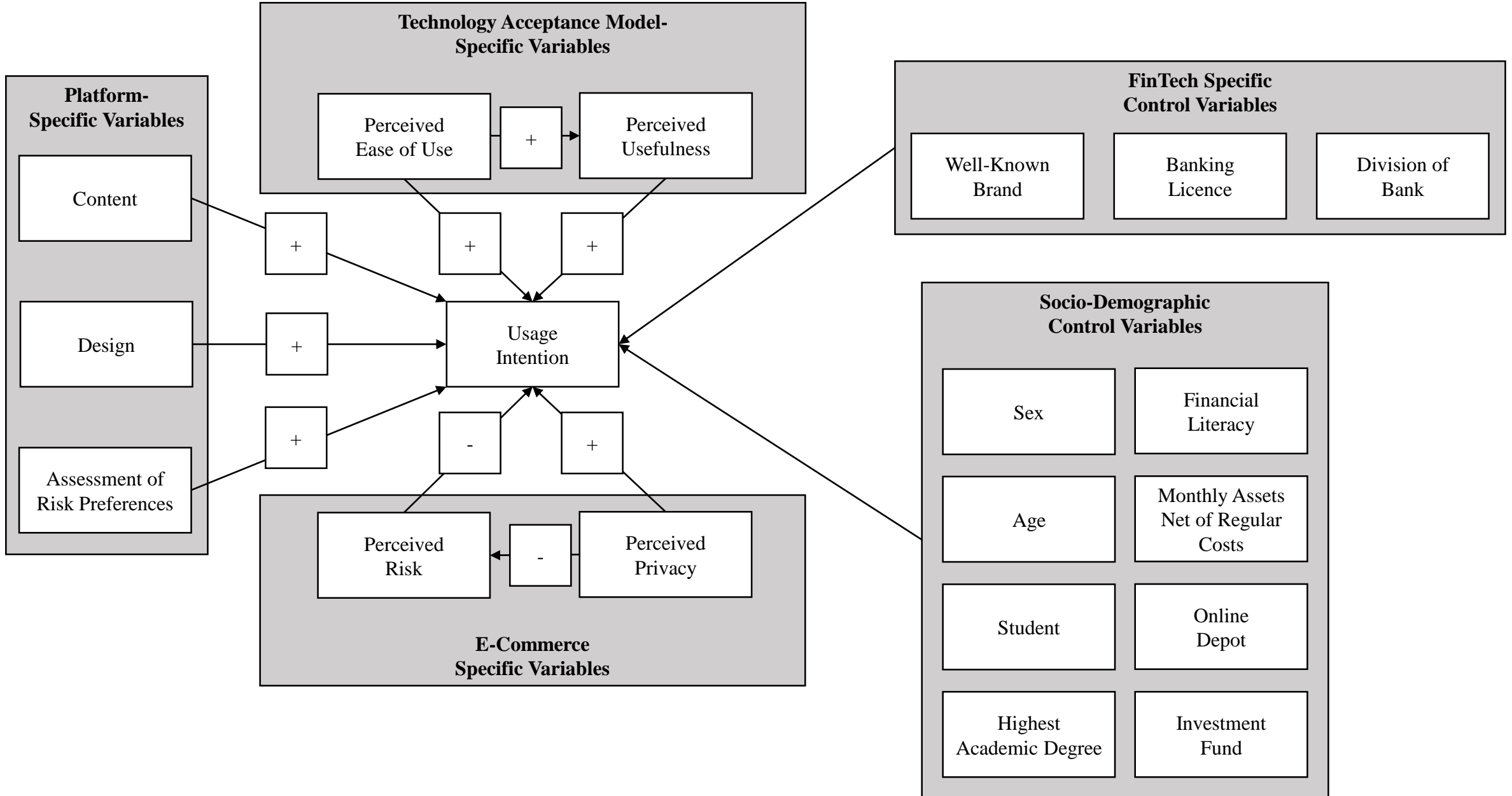
	(1)	(2)	(3)	(4)
Endogenous Variable: Usage Intention				
<i>PEASE</i>	-0.157 (1.075) [0.023]+	-0.133 (0.966) [0.017]	-0.130 (0.949) [0.016]	-0.157 (1.112) [0.024]+
<i>PUSE</i>	0.570 (3.933)*** [0.314]++	0.577 (4.005)*** [0.322]++	0.581 (3.996)*** [0.331]++	0.556 (3.789)*** [0.314]++
<i>CONTENT</i>	0.039 (0.311) [0.001]	-0.016 (0.129) [0.000]	-0.045 (0.364) [0.002]	-0.017 (0.141) [0.000]
<i>DESIGN</i>	-0.088 (0.730) [0.011]	-0.098 (0.013)	-0.118 (0.956) [0.019]	-0.118 (0.974) [0.020]
<i>RISKASSESS</i>	0.001 (0.008) [0.000]	0.045 (0.822) (0.399) [0.002]	0.067 (0.582) [0.005]	0.102 (0.852) [0.011]
<i>PERPRIV</i>	0.227 (1.564) [0.059]+	0.273 (1.693)* [0.089]+	0.304 (1.871)* [0.105]+	0.262 (1.778)* [0.077]+
<i>PERRISK</i>	-0.022 (0.223) [0.001]	-0.000 (0.001) [0.000]	0.005 (0.053) [0.000]	0.006 (0.063) [0.000]
FinTech Controls				
<i>BRAND</i>	0.119 (1.198) [0.022]+			-0.187 (1.900)* [0.054]+
<i>LICENCE</i>		-0.096 (1.073) [0.015]		-0.036 (0.279) [0.001]
<i>BANKDIV</i>			-0.140 (1.537) [0.027]+	0.196 (1.406) [0.023]+
<i>N</i>	96	96	96	96
<i>R</i> ²	0.466	0.461	0.467	0.494
<i>R</i> ² _{adj.}	0.417	0.412	0.418	0.435
<i>Q</i> ²	0.327++	0.322++	0.322++	0.339++

(continued)

Table 6: Baseline Model and FinTech Controls – Continued

	(1)	(2)	(3)	(4)
Endogenous Variable: Perceived Usefulness				
<i>PEASE</i>	0.539 (6.361)*** [0.409]+++	0.539 (6.300)*** [0.409]+++	0.539 (6.247)*** [0.409]+++	0.539 (6.232)*** [0.409]+++
R^2	0.291	0.290	0.290	0.290
$R^2_{adj.}$	0.283	0.283	0.283	0.283
Q^2	0.236++	0.235++	0.235++	0.235++
Endogenous Variable: Perceived Risk				
<i>PERPRIV</i>	-0.374 (3.942)*** [0.162]++	-0.374 (3.850)*** [0.162]++	-0.374 (3.920)*** [0.162]++	-0.374 (3.878)*** [0.162]++
R^2	0.140	0.140	0.140	0.140
$R^2_{adj.}$	0.130	0.131	0.131	0.130
Q^2	0.088+	0.088+	0.088+	0.088+

This table presents the results of the baseline model as presented in Figure 1 adding FinTech controls. Bootstrapped t -values (2-sided test) based on 5,000 Bootstrap samples in parentheses (Efron, 1979). Effect size f^2 in squared brackets. N : Number of observations. Q^2 : Stone-Geisser measure of predictive relevance (Geisser, 1974, 1975, and Stone, 1974); omission distance $D=7$. Variance inflation factors are reported in Table C.2 in the Appendix. ***/**/* indicates statistical significance at the 1%/5%/10% level. +++/++/+ indicates high/medium/small effect size (f^2) and high/medium/small predictive relevance (Q^2), respectively. *PEASE*: Perceived ease of use. *PUSE*: Perceived usefulness. *CONTENT*: Content provided by the robo advisor. *DESIGN*: Design of the user interface of the robo advisor. *RISKASSESS*: Risk assessment. *PERPRIV*: Perceived privacy. *PERRISK*: Perceived risk. *BRAND*: Respondent would be more willing to take advantage of digital investment advice if the robo advisor has a well-known brand. *LICENCE*: Respondent would be more willing to take advantage of digital investment advice if the robo advisor has a banking licence. *BANKDIV*: Respondent would be more willing to take advantage of digital investment advice if the robo advisor is a division of a traditional bank. For FinTech controls, a 5-point Likert-type scale is used, where lower scores indicate a lower agreement with a specific item. The labels are as follows: 1 strongly disagree, 2 disagree, 3 neutral, 4 agree, 5 strongly agree.





26.05.2016

Läuft seit



55,39 €

Portfoliowert



+ 5,39 €

Wertentwicklung



GreenFolio 3

Portfolio



Prognose



Vermögen

81 €

dein erwarteter Wert im August 2032



- Überdurchschnittliche Entwicklung
- Wahrscheinliche Entwicklung
- Unterdurchschnittliche Entwicklung
- Erwartete Entwicklung
- Eingezahlter Betrag

Anlageaufteilung



- 0,00% Geldmarkt
- 19,53% Anleihen
- 80,47% Aktien
- 0,00% Rohstoffe

Ein- oder Auszahlung tätigen

Einzahlung
0 €

Auszahlung
0 €

Komplettverkauf
€→

Eingaben bearbeiten

Mtl. Sparrate
0 €

Jährl. Ratenerhöhung
0 %

Zielbetrag
- €

Zieljahr
-

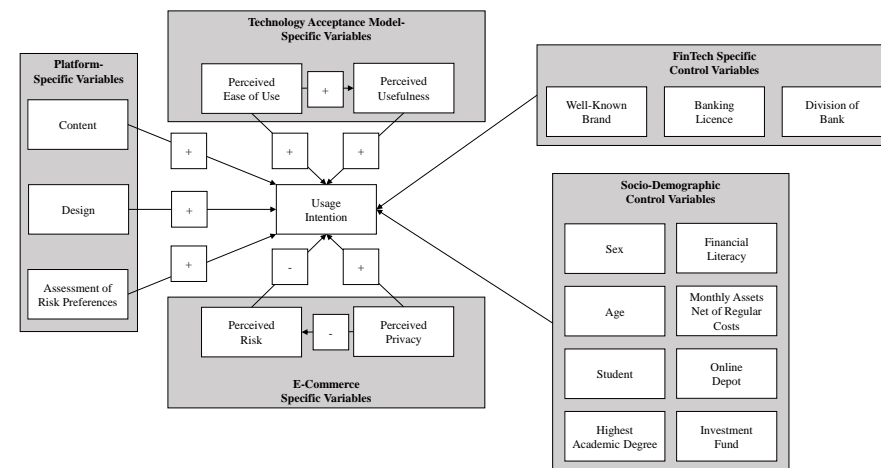
Acceptance of Digital Investment Solutions: The Case of Robo Advisory in Germany

Methodology and Framework for Analysis

Robo advisor replica to make abstract service more tangible



Extended Technology Acceptance Model to assess usage intentions



Data and Results

- Effective sample of 96 participants
- Estimation of model using Partial Least Squares (PLS)
- Intention to use robo advisory mainly driven by perceived usefulness and privacy
 - 1% higher perceived usefulness increases usage intention by 0.57%
 - 1% higher privacy increases usage intention by 0.25%
- Usage intentions are 23%-32% lower for females
- Users of robo advisors tend to be younger, less financially literate and among the lower income brackets