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Completed Research

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Abstract

This study aims at identifying factors influencing robo-advisory demand and usage. We show that it is essential to tell apart the intention to invest in financial markets from the intention to use robo-advisor technology. Therefore, we develop an augmented model of the "Unified Theory of Adoption and Use of Technology" (augmented UTAUT model) that allows to explain both of these customers' intentions simultaneously. The model is evaluated by means of a PLS approach using online survey data collected in the US and Germany. Empirical results shed light on (potential) investors' intentions and attitudes towards robo-advisory services. The model developed in this paper is generally applicable whenever it comes to model adoption of a new technology that relies on the use of a basic product or a basic technology.

Keywords

Robo-advisors, unified theory of acceptance and use of technology (UTAUT), robots, BTA-UTAUT, financial attitudes, financial literacy, consumer survey research, PLS estimation.

Introduction

Robo-advisors (RA) are automated and algorithm-based services to invest on the stock and bond markets without requiring human interaction or judgment. These services are offered by banks, financial advisory firms, or start-ups relying on standardized questionnaires about investors' risk attitudes, investment goals and planning intervals. They provide a recommendation on how to split assets between different classes and offer the asset management to execute the recommendation. As robo-advisory services attract both customers already invested in the capital market and new investors as well, supplying this technology turns out to be attractive in terms of revenue for financial firms, in particular in the current low margin market environment. Hence, determining drivers of robo-advisory demand became a topical issue in consumer research (e.g., Belanche et al. 2019; Hohenberger et al. 2019; Fan and Chaterjee 2020; Todd and Seay 2020; Cheng 2021; Atwal and Bryson 2021).

However, by applying conventional models of technology adoption, none of these studies did assess the dual character of the underlying decision problem: On the one hand the decision to participate in the stock and bond market and on the other hand the decision to use the new technology of robo-advisory.[1]

In our study, we fill this research gap by augmenting the standard model of the "Unified Theory of Adoption and Use of Technology" (UTAUT, Venkatesh et al. 2003) which is widely used in scientific information systems and technology acceptance research, to allow for telling apart customers' decision to invest in financial assets from the decision to use robo-advisor-technology for this purpose. We argue, that disentangling these two decisions and their respective drivers substantially contributes to a comprehensive understanding of private consumers' investment behavior.

The paper is organized as follows: In the next section, we develop a generally applicable "Basic Technology Augmented UTAUT" model. This model is first adapted to robo-advisory demand and then empirically

[1] Some studies excluded participants who do not invest (Fan and Chatterjee 2020; Todd and Seay 2020), while others did not distinguish between both decisions (Belanche et al. 2019).

explored using survey data from the US and Germany. Conclusions are drawn based on the estimation results.

A "Basic Technology Augmented UTAUT" Model

Based on the "Technology Acceptance Model" (TAM, Davis 1989) Venkatesh et al. developed a model representing a "Unified Theory of Acceptance and Use of Technology" (UTAUT, Venkatesh et al. 2003). Their model explains individuals'[2] intention to adopt a new (advanced) technology by four main drivers that proved to be empirically relevant: performance expectancy (defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance"), effort expectancy (defined as "the degree of ease associated with the use of the system"), social influence (defined as "the degree to which an individual perceives that important others believe he or she should use the new system"). The behavioral intention to use a technology and facilitating conditions (defined as "degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system") predict the actual technology usage in the standard model. Additional constructs are added to this model to adapt it to specific contexts and technologies (Venkatesh et al. 2012; Nistor et al. 2014; Belanche et al. 2019).

Even though the UTAUT model became a standard model in empirical technology acceptance research,[3] it does not seem to be perfectly adequate whenever the new technology draws on basic products or a basic technology, the use of which requires a distinct intentional decision of the consumer. Robo-advisors employ new technologies to advise people on which assets to invest in and manage the said investments. But the financial assets that are in the scope of the advice are already established on the market (basic products). They are also the subject of advice of conventional financial advisors. Hence, consumers face a dual decision problem and it is important to notice that the two steps of technology adoption are indeed subject to distinct decisions. Therefore, the technological innovation of robo-advisors only consists in the advice delivery and the way that assets are managed, but not the assets themselves.

As this dual choice concerning basic technology or basic product and new technology is not restricted to explaining robo-advisory adoption (we address some related examples below), we tackle this problem in a general setting to begin with. To deal with the dual character of the adoption decision properly, the dependence of the intention to use the new/advanced technology on the intention to use the basic product or technology has to be modeled explicitly. Even though a distinct logical hierarchy between both choices does exist, the respective consumers' decisions may be reached simultaneously. Moreover, the choice to use the basic technology may depend on distinct exogenous drivers. Hence, we augment the classical UTAUT model by the intention to use the basic product or technology as illustrated in Figure 1.)

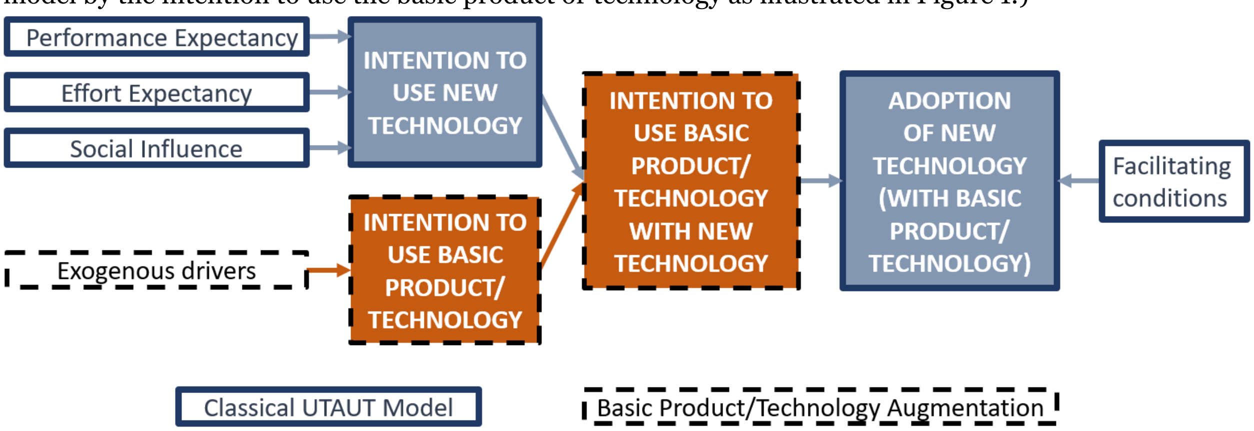

Figure 1. Basic Technology Augmented UTAUT (BTA-UTAUT) Model

[2] Both TAM and UTAUT were originally developed in the context of business organizations and were later adapted to the consumer context.

[3] UTAUT has been successfully applied in numerous fields, e.g., mobile internet adoption (Venkatesh et al. 2012), and mobile banking adoption (Zhou et al. 2010; Yu 2012).

Designing robo-advisors appropriately calls for reliable estimates of customers' attitudes. Figure 1 illustrates that estimated effects of classical UTAUT drivers on adoption may suffer from misspecification bias, whenever the intention to use the basic technology also turns out to be relevant for customers, entailing potentially misleading management decisions. Figure 1 does also reveal an intuitive approach to empirically test for the adequacy of the BTA-UTAUT model: Whenever data allow to significantly estimate individual effects of both, the intentions to use the new and the basic technology on adoption (i.e., on the construct measuring the intention to use the basic product by means of the new technology) BTA-UTAUT dominates the conventional UTAUT model and should lead to more reliable results for management decisions. The BTA-UTAUT model can generally be applied in settings where a) a basic technology is necessary to use the new technology and b) this basic technology is not omnipresent, like, say, electricity in most developed countries. The latter condition makes sure that choosing to use the basic technology or product is a genuine decision for consumers. Hence, the BTA-UTAUT model may be applied to related problems in consumer finance (adoption of NFC technology based on usage of NFC-enabled smartphones), consumer electronics (adoption of VR equipment based on the usage of game consoles) or even development economics (adoption of digital (micro) banking based on smartphone usage), just to name a few. Thus, the BTA-UTAUT model is applicable as long the basic technology has not become a commodity for the population in question. In cases where the technology is so widespread that its availability does not influence behavior (as electricity and internet access in very developed countries), it makes more sense to use classic UTAUT models to study the adoption of a new technology.

In the particular context of this study, it could be argued that intention to use the new technology does not have to be measured independently as the adoption of robo-advisor advice directly depends on the willingness to invest on the stock market. Nevertheless, we have decided to include the intention to use new technology as an independent construct as such a distinction proves to be vital for some technologies. Consider the case of digital (micro) banking already mentioned above: Smartphones are a new way to make micro banking available to households without access to banking products. But alternative modes of distribution of the micro banking products are possible and even established (e.g., 7-Eleven Mexico allows customers who have no credit or banking cards to pay for online purchases in their stores). Therefore, the intention to adopt micro banking would have to be specified independently from the intention to use micro banking with a smartphone. In the subsequent empirical analysis, we find that our data indicate that even in the context of robo-advisory the two concepts (intention to use new technology and intention to use basic technology with new technology) are indeed distinct (see results). Moreover, they turn out to be rather useful as they allow the analysis of opposing effects of independent constructs on the adoption intentions of new and old technology which otherwise would be impossible. The measurement items used for the adoption intention constructs of the BTA-UTAUT are derived from the established UTAUT adoption intention items.[4]

For the robo-advisory case, we have to specify a) additional specific constructs affecting the adoption intention of the advanced technology of robo-advisory and b) constructs driving the intention to invest in financial assets (basic products). All constructs included in the research model to drive the adoption intention of the new technology and the basic product are based on established constructs and measurement items. Therefore, we refrain from citing the measurement items used and refer to the cited references that the constructs are derived from. Upon request, the authors will provide a complete list of the measurement items used.

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[4] Intention to invest (IINV) corresponding to the general concept intention to use the basic product: *"I intend to invest on the stock market in the future"*, *"I will try to invest on the stock market regularly"*, and *"I plan to invest on the stock market frequently"*; Intention to use robo-advisors (IURA) derived from the general concept intention to use the new technology: *"I would intend to rely on recommendations from a robo-advisor if I invested on the stock market"*, *"I would regularly try to invest relying on recommendations from a robo-advisor if I invested on the stock market"*, and *"I would plan to invest relying on recommendations from a robo-advisor if I invested on the stock market"*; Intention to invest using a robo-advisor (IIRA) based on the general concept intention to adopt the new technology with the basic product: *"I intend to invest on the stock market with a robo-advisor in the future"*, *"I will try to invest on the stock market with a robo-advisor regularly"*, and *"I plan to frequently invest on the stock market with a robo-advisor"*.

Concerning additional technology-related drivers we consider the construct of personal innovativeness to describe the willingness of an individual to try out any new information technologies. Personal innovativeness (see Agarwal and Prasad 1998) has been included in different papers in various TAM/UTAUT models.[5] We assume that personal innovativeness can play an important role for robo-advisor adoption as its effect on the adoption of financial technology was demonstrated for mobile payment in China (Yang et al. 2012).

Moreover, we include a construct accounting for perceived privacy risk (see Featherman and Pavlou 2003) defined as "potential loss of control over personal information, such as when information about you is used without your knowledge or permission."[6] Perceived privacy risk is added to the model as it was shown in several studies (e.g., Lee 2009; Lu et al. 2011) to influence the adoption of the financial technology of online banking suggesting that it might also influence robo-advisor adoption. Furthermore, evidence from interviews with German investors suggests an influence of privacy risk on robo-advisor adoption intention (Atwal and Bryson 2021).

Finally, investable funds can be seen as an essential resource to invest in stocks and hence serve as a facilitating condition in the context of our study. The positive impact of household wealth on stock market participation was demonstrated in the major European economies (Guiso et al. 2002) and the USA (Bertaut 1998). Therefore, household wealth is assumed to predict the actual investment behavior, i.e., real investments using a robo-advisor technology. Furthermore, as many robo-advisors require a minimum investment to open an account, investable funds can be seen as a necessity to use them.

With respect to the basic technology, we consider three constructs influencing the decision to invest in financial assets: First, financial literacy is defined as "a measure of the degree to which one understands key financial concepts and possesses the ability and confidence to manage personal finances through appropriate, short-term decision-making and sound, long-range financial planning, while mindful of life events and changing economic conditions" (Remund 2010). The positive influence of self-assessed financial experience on the willingness to use robo-advisors in an online sample of American adults resulted in a call for more research involving objective financial literacy (Hohenberger et al. 2019). The negative effect of financial literacy on robo-advisor adoption (Fan and Chatterjee 2020; Todd and Seay 2020) is especially interesting as it does not correspond to most studies showing a positive influence on stock market participation (Van Rooij et al. 2011) and reliance on financial experts (Lusardi and Mitchell 2011). Therefore, we assume that the influence of financial literacy on the basic and new technology (stock market participation and robo-advisor adoption) are diverging.

We also account for the ethical stance towards the stock market (see Webley et al. 2001; Keller and Siegrist 2006). A negative ethical stance towards the stock market was established as a factor predicting the willingness to invest in stocks in a sample of 1500 Swiss study participants (Keller and Siegrist 2006). Therefore, we concluded that the inclusion of this construct could explain the intention to invest on the stock market, i.e., the basic technology in our study. A negative ethical stance towards stocks was arguably rooted in the view that profits from stocks are not acquired by work and achievement (Keller and Siegrist 2006). This approach offers interesting insights in the scope of this study as it directly focuses on the moral attitudes towards the stock market and the products invested in. Following this approach can elicit the moral judgment that potential investors have towards the stock market irrespective of their decision whether to invest on their own or use a robo-advisor.

Third, we account for the financial risk attitude measuring the acceptance of incurring potential financial losses. Financial risk attitude was a good predictor of the willingness to invest in stocks among Swiss participants (Keller and Siegrist 2006), i.e., equivalent to the adoption intention of the basic product in this study. Loss-aversion reduced household participation in equity markets in data from the Dutch CentERdata DNB Household Survey (Dimmock and Kouwenberg 2010). As risk attitude in the context of this paper is supposed to predict intention, the items of the psychometric measure are adapted from existing literature (Pennings and Smidts 2000). Finally, we detail social influence by interpersonal and external influence (see

[5] Personal innovativeness showed an effect on perceived usefulness and perceived ease of use through the psychological variable cognitive absorption for the internet usage of American students (Agarwal and Karahanna 2020).

[6] Security and privacy risks include fraud or hacking of an online user's account and phishing of data (Reavley 2005).

Belanche et al. 2019) and include age, gender, income, and education as moderating control variables in the model.[7] The complete research model including conjectured signs of impacts is presented in Figure 2.)

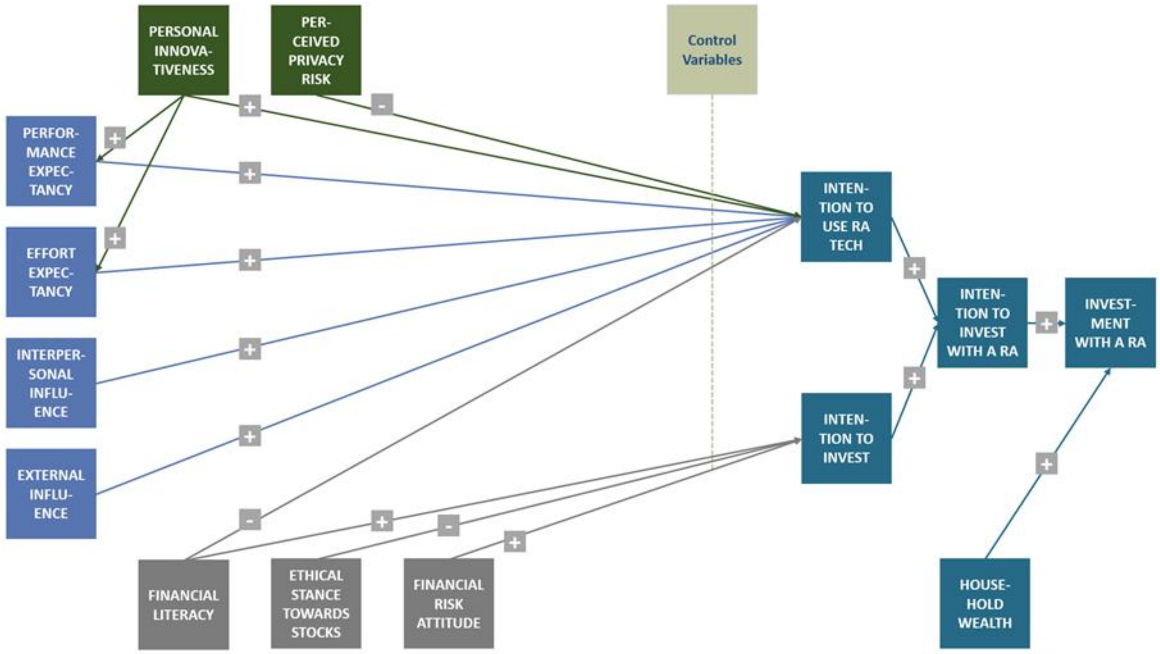

Figure 2. BTA-UTAUT Model for Robo-Advisor Adoption

Empirical Methodology

Data

Data were collected to empirically assess the BTA-UTAUT model employing an online survey conducted on Amazon Mechanical Turk with 1093 participants in the USA in June 2021 and on Clickworker with 1102 participants in Germany in July 2021. As Germans participate less in the stock market (Crédit Suisse Global Wealth Report 2020) and robo-advisor investments (Dorfleitner and Hornuf 2021) than Americans, Germany can be regarded as a less mature market than the USA.

A questionnaire was created to appropriately measure the latent constructs and the control variables as well. As explained in the previous section, we used items already established in the psychometric literature. The operationalization of the constructs specific to the BTA-UTAUT was detailed above (see footnote 4). The specific items and the literature we draw on is issued on request by the authors. Data quality was enhanced using instructional manipulation checks (see Oppenheimer et al. 2009) leaving 998 in the US and 1059 in the German sample for further analysis.

Due to the sampling procedure, our sample is not representative neither for US nor for German citizens. Therefore, we point out the explorative character of our study. The descriptive characteristics of the sample, however, do corroborate the stylized facts on investment behavior and wealth in the US and Germany outlined above as 44.5% of the American sample, but only 3.9% of the German sample were invested in robo-advisors. Both samples had a mean age of 37.8 years, while 39.9% of the US sample and 44.5% of the German sample identified as female.

[7] Moderating variables proved to be relevant in various studies on technology adoption in general and on financial choices as well: Gender was confirmed to influence the role of others' opinions on the adoption decision, while younger age was associated with a higher importance placed on performance expectancy (Venkatesh et al. 2003). Education was confirmed to have a positive impact on stock market participation (Guiso et al. 2002).

Estimation Methods

Data were analyzed using partial least squares (PLS) regressions with the software SmartPLS 3. The model was measured using the consistent PLS algorithm with additional analyses conducted with the consistent PLS bootstrapping with 5000 subsamples. All reflective constructs were measured using Mode A and the formatively specified construct of financial literacy was measured using Mode B. In the final measurement model, both the US and the German sample rho_alpha measuring construct reliability consistently exceeds the 0.707 threshold indicating that more than 50% of the variance of the construct scores are accounted for by the latent variable (Benitez et al. 2020; Nunnally and Bernstein 1994). Discriminant validity is measured by the Heterotrait-Monotrait Ratio (HTMT) (Henseler et al. 2015) which has a recommended conservative threshold of 0.85 (Voorhees et al. 2016) or lenient threshold of 0.9 (Henseler et al. 2015). The range of values showed discriminant validity for all factors.[8] This shows, as discussed above in the preceeding section, that in the case of robo-advisors and with this participant pool the constructs of intention to use robo-advisor technology and the intention to invest with a robo-advisor prove to be not only theoretically, but also empirically distinct concepts. The weights and loadings of all indicators are highly significant and have the expected sign. Evaluation and adjustment of the measurement model can be received from the authors upon request. Concerning the control variables, direct and moderating effects were included to the model sequentially and retained when significance was reached at the p<0.05-level. All remaining effects of the sequential tests were tested together and all effects that did not reach the p<0.05-significance level were removed.

Results

Estimation results for the US and the German model are reported in Figure 3.) and Figure 4.), respectively.[9]

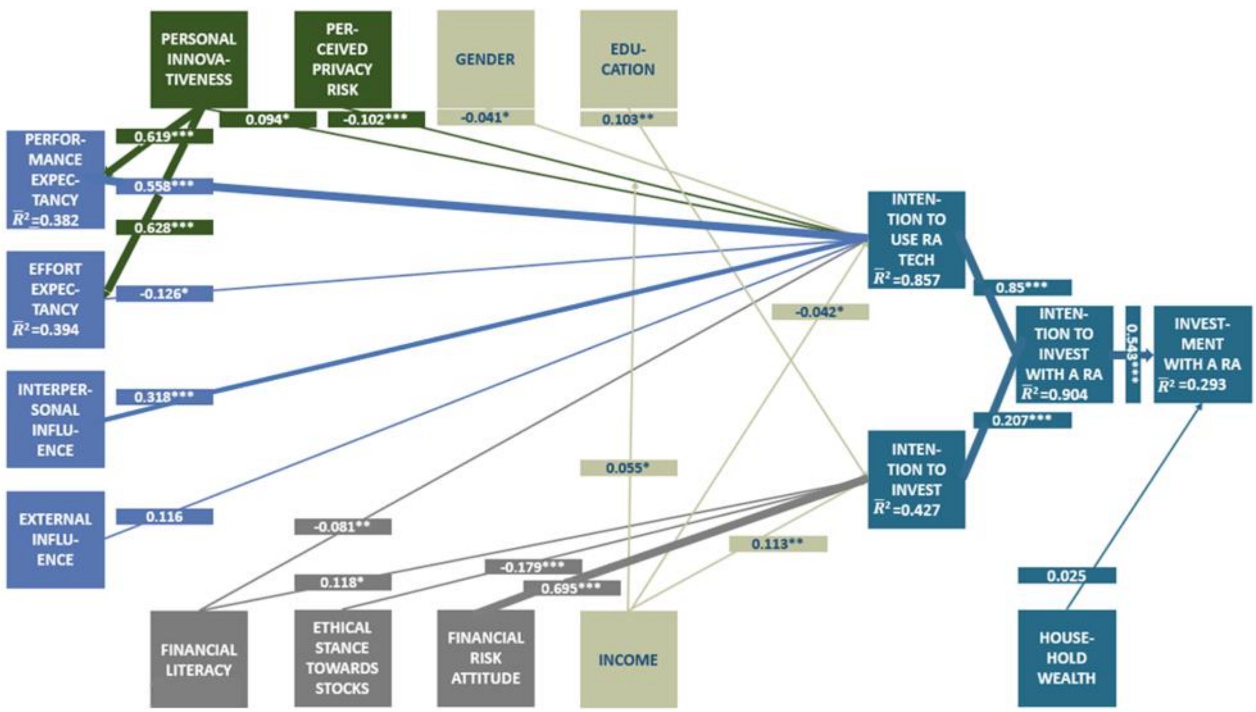

Figure 3. Path Coefficients, Statistical Significance and Effect Sizes, US Model

Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Effect size: Cohens $f^2 < 0.1$, $0.1 <$ Cohens $f^2 < 0.3$, Cohens $f^2 > 0.3$.

[8] Financial literacy is the one and only composite construct in the model. Here, we faced no problem of multicollinearity (all VIF values were below 5).
[9] Detailed estimation results can be received from the authors.

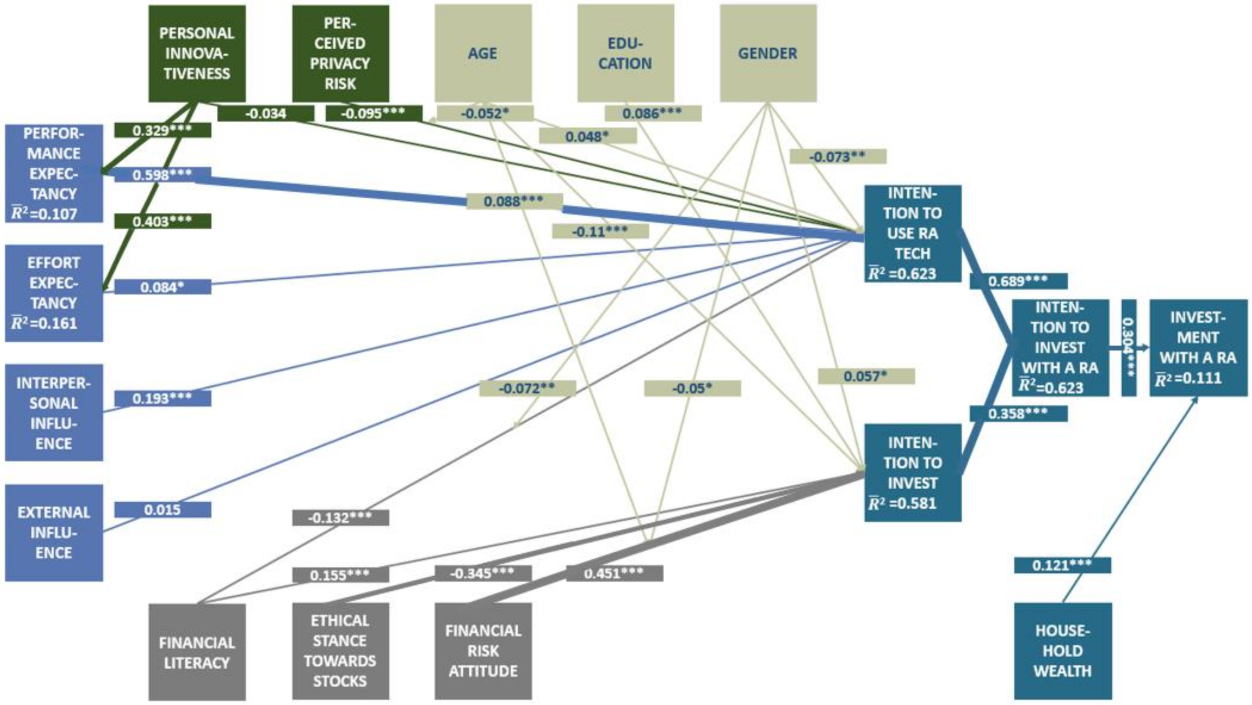

Figure 4. Path Coefficients, Statistical Significance and Effect Sizes, German Model

Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Effect size: Cohens $f^2 < 0.1$, $0.1 <$ Cohens $f^2 < 0.3$, Cohens $f^2 > 0.3$.

Concerning the "core model" describing interrelations between the behavioral intentions and the usage of robo-advisors, path coefficients of the latent variables intention to invest (IINV) and of the intention to use the technology of robo-advisors (IURA) to the intention to invest using a robo-advisor (IIRA), are significant to the p<0.001 level in both models. The same holds true for the influence of IIRA on actual investment with a robo-advisor. Moreover, the "core" effect sizes as measured by Cohen's f^2 (IINV on IIRA, IURA on IIRA, and IIRA on robo-advisor investment) are large. For the German sample we find smaller effect sizes, where the weak effect size of IIRA on actual robo-advisor investment might be caused by the rather low share of German respondents using robo-advisors.

Perceived privacy risk negatively affects the intention to use robo-advisor technology in both samples (p<0.001) with small effect sizes. For the US, income has a significant moderating effect (p<0.05) with a small effect size on the influence of perceived privacy risk on the intention to use robo-advisor technology, such that the negative effect of perceived privacy risk becomes smaller with higher income. The role of personal innovativeness is more pronounced in the US, as it significantly and strongly raises both performance expectancy and the intention to use robo-advisors and - to a lower extent - effort expectancy. In both samples, financial literacy exerts differentiated effects on robo-advisor adoption: It proves to have a positive effect on the intention to invest on financial markets (IINV) while it reduces the willingness to draw on robo-advisor technology (IURA). However, effect sizes tend to be small. Ethical stance towards the stock market highly significantly affects the intention to invest IINV, with a larger effect size in Germany than in the US.

Our results do support the BTA-UTAUT model for robo-advisor adoption in a number of aspects:

- Both, technology acceptance related constructs (i.e., personal innovativeness and privacy risk perception) and the measures for financial attitudes (i.e., financial literacy, financial risk attitude and ethical stance towards the stock market) as well, significantly contribute to modeling robo-advisor adoption.
- Disentangling technology acceptance (as measured by personal innovativeness, privacy risk perception and the standard UTAUT drivers) and financial attitudes (as measured by financial literacy, financial risk

attitude and ethical stance towards the stock market) lead to significant individual effects of the intention to invest and the intention to use robo-advisory services on the intention to invest using robo advisors.

- The BTA-UTAUT model allows to consistently pin down diverging effects on the intention to invest (i.e., to use the basic product/technology) and the intention to use robo-advisors (i.e., to use the new technology) at the same time, while previous studies could merely reveal but one of these contradicting effects. While a positive effect of financial literacy on the intention to invest is documented in the literature (Van Rooij et al. 2011; Lusardi and Mitchell 2011), financial literacy showed a negative effect on the willingness to use robo-advisors (Fan and Chatterjee 2020; Todd and Seay 2020). For the US sample, the BTA-UTAUT model corroborates findings reporting a positive effect of income on stock market participation (Lusardi and Mitchell 2011) on the one hand and results finding that higher incomes were negatively related to robo-advisor adoption on the other hand (Fan and Chatterjee 2020; Todd and Seay 2020). Thus, measuring diverging effects of constructs on the adoption intention of basic and new technology helps to solve puzzles previously documented in the literature.
- Model fit is increased when breaking up robo-advisory adoption into both aspects, intention to invest (i.e., to use the basic product/technology) and intention to use robo-advisors (i.e., to use the new technology), as can be verified by comparing the respective R^2-values for the intention to invest with robo-advisors in the UTAUT vs. the BTA-UTAUT specification, see Table 1.)[10]
- The latter effect carries over to the models' predictive abilities: We used the PLSpredict procedure (Shmueli et al. 2016) to assess the models' out-of-sample predictive power.[11] The Q^2 statistic measures the models' ability to "outperform the most naïve benchmark, defined as the indicator mean from the holdout samples" (Sarstedt et al. 2021) and is positive for both samples, markedly larger for the US than for Germany, see Table 1.)

Model	Measure	US Sample	German Sample
UTAUT	R^2	0.868	0.592
BTA-UTAUT	R^2	0.904	0.623
	ΔR^2	0.036	0.031
BTA-UTAUT	Q^2	0.244	0.045

Table 1. Goodness of Fit and Predictive Power Comparisons

Conclusion

We argued that it is essential to differentiate between the intention to invest in financial markets and the intention to use robo-advisors to model robo-advisor adoption. As conventional models of technology adoption do not distinguish these behavioral intentions, we augmented a conventional UTAUT model. The "Basic Technology Augmented" BTA-UTAUT model allows to discriminate both effects. The general specification of this model can be applied whenever adoption of a new technology requires the acceptance of an underlying basic technology or product which cannot yet be considered a commodity in the specific market, some examples were given.

The BTA-UTAUT model for robo-advisor adoption was validated using online survey data and PLS estimation led to sensible results for the US (mature market) and Germany (evolving market). By unveiling consumers' attitudes, estimation results can support management decisions on the design of robo-advisors. Therefore, we plan to explicitly address the relationship between particular features of robo-advisors' design and the BTA-UTAUT constructs in future research.[12] Finally, we point out the explorative character of our study as our data might not be representative. Further research based on adequate random samples shall allow for a more rigorous analysis of the BTA-UTAUT model.

[10] Note that „Intention to invest using RA“ equates to „Intention to use RA“ in the basic UTAUT model.
[11] A 10-fold cross-validation with ten repetitions was chosen (Shmueli et al. 2019).
[12] This issue was addressed by means of survey data and hierarchical regressions in a recent study (Wu and Gao 2021).

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