Can I Control My Robo-Advisor?  
Trade-Offs in Automation and User Control in (Digital) Investment Management

Completed Research

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Abstract

Owing to technological advancements, individuals can increasingly automate and delegate private decisions. However, prior research shows that decision-makers tend to prefer human decision support despite the superiority of algorithms. Further, individuals prefer retaining control of decisions despite increased effort. We propose a model explaining underlying considerations of these paradoxes in decision support acceptance. In a vignette-based experiment in the context of investment management, we test the model to explain trade-offs in varying levels of automation and user control and analyze effects on the intention to utilize decision support. Results provide support for a positive effect of automation on performance expectancy and a negative effect of user control on perceived risk. These findings support the idea of increased automation in decision-making while letting users retain control over the process. This study extends our understanding of decision support in private contexts and holds implications for providers of decision support systems, particularly robo-advisors.

Keywords

Automation, user control, decision support, robo-advisory, autonomous systems.

Introduction

Evolving advancements in processing power and the utilization of data enable the emergence of a new - cognitive - generation of decision support systems (DSSs) (Watson 2017). Consequently, the scope of decisions supported or executed by algorithms has increased. Moreover, due to the remote accessibility of storage and processing power facilitated by increasing connectivity, algorithmic decision support is extending to private decisions. Streaming platforms can recommend users suitable movies to watch (Lu et al. 2015) and robo-advisors can advise customers on the ideal investment portfolio (Jung et al. 2018). In parallel to the diversification of application areas, the level of independence of decision support has steadily increased, decreasing both necessity and possibility of human intervention. While earlier systems suggested solutions, today's systems automate entire decision processes and turn decisions into actions autonomously (Schaefer et al. 2016). This evolution has been subject to user skepticism (Złotowski et al. 2017).

Why is that? Research on the acceptance of algorithmic decision support has yielded two paradoxes that we aim to integrate and clarify in this study. On the one hand, despite the superiority of algorithmic conduct in various tasks (Grove et al. 2000; Harvey et al. 2017; Kleinberg et al. 2017), users tend to prefer human conduct (e.g. Diab et al. 2011). On the other hand, despite the decrease in required effort with a task when delegating it to someone else (van der Heijden 2003), people tend to prefer to delegate only parts of a task and retain partial control (Rijsdijk and Hultink 2003). These paradoxes suggest the importance of two determinants for the acceptance of algorithmic decision support: the extent to which the support is automated (rather than provided by a human) and the amount of control a user retains. Previous studies have investigated either the automation (e.g. Diab et al. 2011) or the control consideration for the
acceptance of decision support (e.g. Barkhuus and Dey 2003), yet only in isolation. We argue that a comprehensive investigation of acceptance must evaluate both parameters. Therefore, we pose the research question:

RQ: Which effect do the level of automation and the level of remaining user control exert on the intention to use decision support?

We propose a research model integrating key trade-offs underlying the effects of the levels of automation and user control. To confront participants with decision support characterized by different combinations of levels of automation and user control, we use vignette-based illustrations of service offerings in investment management. These services range from traditional human advisors to fully automated robo-advisors. In a subsequent survey, participants are asked to state their perceptions of the respective service and their intention to use it. The information from the survey allows us to determine to what extent the trade-offs of the levels of automation and user control explain the intention to utilize decision support.

By investigating the appreciation of decision automation and user control in a private context we add to existing theory explaining the acceptance of DSSs. Moreover, we contribute to the design of DSSs with implications on the ideal levels of automation and user control. In the remainder of this paper, we introduce the automation and user control parameters and the context of investment management, particularly robo-advisory. We derive and test our research model, before discussing results, implications to theory and practice, as well as limitations and future research opportunities.

Theoretical Foundations

Levels of Automation and User Control: Trade-offs in Decision Support

Considerations of the use of decision support are dependent on two parameters. One parameter - the level of automation - is concerned with the extent to which algorithms conduct decisions as opposed to human conduct. The parameter varies from entirely human conduct in decision support to entirely algorithmic processes. The second parameter - the level of user control - is concerned with the extent of control a user retains in the decision process. In the highest extent, users would conduct the entire process themselves. The lower the level of user control, the greater the share of the process that is conducted on behalf of the user. Since the parameters are conceptually close, this section further elaborates their distinction.

Automation refers to the full or partial accomplishment of a function by a system that could be performed by a human (Parasuraman et al. 2000). More explicitly, it refers to “technology that actively selects data, transforms information, makes decisions, or controls processes” (Lee and See 2004, p.50). The level of automation can be measured depending on the extent of algorithmic conduct in the stages of information processing comprising information acquisition and analysis, decision-making and action (Parasuraman et al. 2000). Prior research has shown severe differences in human perception of automation. Individuals are averse towards higher levels of automation, when they consider human intuition important for task performance (Highhouse 2008). On the contrary, individuals perceive automated processes as more appropriate than human conduct for tasks relying on objective information processing (Logg et al. 2019). Besides performance expectations, the perception of risk influences the attitude towards automation as higher levels of automation have been shown to lead to a stronger perception of risk (Martins et al. 2014).

Conversely, higher levels of user control have been shown to decrease the perception of risk, leading to the interaction of automation and user control. When delegating a task, one entrusts this task to a third party, enabling the completion through the action of a delegate (Castelfranchi and Falcone 1998). Yet, the delegator can no longer control all aspects of that task. Considering whether to delegate, therefore reducing one’s own control, has been subject of extensive investigation in human-to-human delegation (Calcagno and Monticone 2015; Leana 1986) but also in the delegation of humans to software agents (Milewski and Lewis 1997). Prior literature finds that individuals tend to delegate too little to optimally utilize their resources and that the severity of this phenomenon depends on their characteristics, the delegate’s characteristics and situational factors such as the importance of a task. This applies to delegation to both humans and software agents. The higher the level of delegation, the less control remains with the delegator. This absence of control can be perceived positively, due to the decrease in effort when a task is delegated (van der Heijden 2003). It can also be perceived negatively, in the form of higher risk, i.e. a higher perceived likelihood of the delegate and therefore the task to fail (Rijsdijk and Hultink 2003).
Automation and User Control in (Digital) Investment Management

(Digital) Investment Management

To investigate the effect of levels of automation and user control on the consideration to utilize decision support, investment management is a particularly suitable context. Digital investment management systems, referred to as robo-advisors, are applications that can digitalize the entire process of investment management (Jung et al. 2018), facilitating the investigation of services ranging from human to automated decision-making with varying levels of user control. Investment decisions allow for the investigation in a private rather than a professional setting and render a high error severity due to potential losses of private capital. This increases the likelihood of participants to reveal their true preferences. Although mobile accessibility of robo-advisors would allow user control in decision processes, many providers do not grant control. Compared to recommender systems identifying preferences to make recommendations (Xiao and Benbasat 2007), robo-advisors constitute the development towards autonomous execution of such.

Due to the ability to process user and market data in real-time and support private decisions, technological advancements in robotics and decision support are well represented by robo-advisors. Robo-advisors can be considered robots, virtually rather than physically embodying actions in investment management (Jung et al. 2019; You and Robert 2018). Recent IS literature has primarily discussed effects of physical robot characteristics and expressions (e.g. Blut et al. 2018; Stock 2018), their personality (Robert 2018) and varying usage conditions and contexts (Thimmesch-Gill et al. 2017) on human-robot interaction. Here, we focus on parameters affecting the interaction with virtual robotic abilities.

Investment management services can be categorized along the parameters of automation and user control. We distinguish between a human and an algorithm level of decision conduct and differentiate between partial and no control. The process of investment management can be aggregated to three core steps (Cocca 2016; Rühr et al. 2019). Creation of a risk profile, development of a portfolio, and portfolio maintenance. While human managers identify risk profiles in personal conversations, robo-advisors use standardized questionnaires. To predict the market and build portfolios human advisors rely on experience, while robo-advisors apply simulation techniques and algorithms. To balance risk preferences and portfolio risk, robo-advisors monitor portfolios in real-time, while human advisors monitor on a regular, yet discrete basis.

Hypotheses Development and Research Model

Core to this study are development and test of a model representing the explanatory capacity of two trade-offs in automation and user control on the usage intention for robo-advisors. We hypothesize increased perceived automation to pose a trade-off between performance gains associated with superior algorithmic conduct and increased perceived risk associated with algorithmic decision-making. Increased perceived user control is hypothesized to decrease perceived risk at the cost of increased task complexity (Figure 1).

![Figure 1. Integrated Research Model](image)

**Direct Effects on Intention to Use**

IS literature has shown that the expected performance of a technology has a highly significant positive influence on the behavioral intention to use that technology (Venkatesh et al. 2012). Similarly, advice literature has shown that the quality of an advice is a positive determinant of advice utilization (Yaniv and Kleinberger 2000). Therefore, the positive relationship of expected performance and the behavioral intention to use is likely to hold for human investment management as well as for robo-advisory.

**H1a:** Performance expectancy positively affects the intention to use.
Numerous studies have proven a significant negative impact of the perception of risk on the behavioral intention to use a system (e.g. Featherman and Pavlou 2003; Martins et al. 2014). Furthermore, in the context of personal financial decision support, a context with a high degree of task importance, the negative relationship is known to be particularly prevalent explained by increased caution of customers with decisions regarding their personal finances (Lee 2009).

**H1b: Perceived risk negatively affects the intention to use.**

Task complexity is determined by the effort associated with a task. From investigations in technology acceptance, we know that the effort associated with the use of a technology acts as a hurdle to the behavioral intention to use that technology (e.g. Venkatesh et al. 2003). In accordance to the conceptualization of task complexity applied in this study (Maynard and Hakel 1997), task complexity is driven by the effort associated with the investment management task. The higher the expected complexity of that task when aided by the investment management system, the lower the intention to use that system.

**H1c: Task complexity negatively affects the intention to use.**

**Trade-offs in Levels of Automation and User Control**

Performance expectancy in the context of technology acceptance is defined as the “degree to which using a technology will provide benefits to consumers in performing certain activities.” (Venkatesh et al. 2012, p.159). Evidence suggests that algorithms outperform humans in many application areas, e.g. in business decisions (Tazelaar and Snijders 2013) and medical decisions (Grove et al. 2000). Especially, in contexts that require objective information processing, such as investment management, individuals may perceive automated conduct as more appropriate than human conduct (Logg et al. 2019).

**H2: Perceived automation positively affects performance expectancy.**

Users perceive services with higher levels of automation as less flexible (Diab et al. 2011) and less able to apply intuitive judgement to their tasks (Highhouse 2008). The limited flexibility decreases the ability to react to changes and therefore increases the probability of a deviation from the ideal outcome, which translates into an increased perception of risk. The perception of risk due to increased levels of automation has been shown in numerous studies, especially the context of financial services (e.g. Martins et al. 2014). Such risk perceptions span from performance to financial risks and security risks.

**H3a: Perceived automation positively affects perceived risk.**

The level of user control determines to what extent the user can intervene with the actions of a DSS. In the condition of partial control, the user can choose to intervene. In case of no control, the user cannot intervene with the actions suggested by the system (van der Heijden 2003). As such actions determine the outcome of the underlying task, the perceived likelihood for an undesirable or unintended outcome decreases with increased user control (Das and Teng 1998). Opposing the concept of control, system autonomy describes the level of independence from user participation. As the level of autonomy increases, so does the diversity of tasks a system performs. The more diverse the tasks, the higher the likelihood of failure in aspects of task completion, leading to increased perceived risk (Rijsdijk and Hultink 2003). Further, the higher the level of autonomy, the more likely the failure to meet user expectations, leading to undesired outcomes and the perception of risk (Castelfranchi and Falcone 1997).

**H3b: Perceived user control negatively affects perceived risk.**

One of the main components of perceived task complexity are the required actions and therefore the effort associated with successfully fulfilling a task (Wood 1986). Complexity increases if these actions require substantial mental effort (Maynard and Hakel 1997). Increased user control implies a decrease in the number of tasks conducted on behalf of the user, hence an increase in the requirement for actions on part of the user (van der Heijden 2003). The more control of decisions and actions remains with the user, the more he is obliged to act in the pursuit of a successful task completion himself, leading to a higher perceived task complexity.

**H4: Perceived user control positively affects task complexity.**
Methodology

Experimental Design

To test the hypotheses and establish the model, we conducted a vignette-based online experiment in the context of investment management. After an introductory scenario, we randomly assigned participants to one of four vignettes and subsequently presented them a post-vignette survey on the perception of and intention to use the displayed investment manager. In the introduction, we asked participants to put themselves in the position of a young adult who saved up 5,000€ as a long-term asset. In the vignettes, we presented participants with three options to invest the savings. Besides the possibility of keeping the money in a bank account or investing it by themselves, participants faced one of four investment management alternatives in accordance to distinct combinations of levels of automation and user control (Table 1). Scenario and graphical illustrations were identical over all groups to prevent a bias towards one alternative.

<table>
<thead>
<tr>
<th>Level of automation</th>
<th>Level of user control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algorithm</td>
<td>Algorithmic advice (1a)</td>
</tr>
<tr>
<td>Human</td>
<td>Human advice (2a)</td>
</tr>
</tbody>
</table>

Table 1. Combinations of Levels of Automation and User Control in the Vignettes

We introduced the two groups in the high automation domain (1a and 1b) to a robo-advisor and the the two groups in the low automation domain (2a and 2b) to a human investment manager. We provided short descriptions of functionality and approach, which differed only in the description of the decision-making process as conducted by algorithms or humans. We manipulated user control such that one group on each level of automation had the opportunity to partially control the investment decisions (1a and 2a). In this condition, we informed participants that they had to approve or adjust each process step outcome. The groups with no control (1b and 2b) faced fully autonomous management using the results of one process step directly as input for the next one. We derived the described approaches from archetypical investment advisory processes described in academic and practitioner literature (Jung et al. 2018; Rühr et al. 2019).

We applied a vignette design with textual and graphical elements as it mimics the information acquisition when identifying investment alternatives and allows isolation of the effects of different levels of automation and user control from the range of other effects (Atzmüller and Steiner 2010). We confronted participants with a fictitious scenario and asked them to make judgements or decisions in reaction (Aguinis and Bradley 2014). This design was particularly suitable, as we were able to display algorithmic and human decision support with similar functionalities realistically. That allowed us to measure the impact of variables that are otherwise difficult to operationalize in laboratory settings such as levels of automation and user control.

To account for the diversity in perceptions of automation and control, we followed the approach of Lowry et al. (2013), suggesting the use of perceptions of treatment parameters rather than binary treatment variables. Besides incorporating the diversity of perceptions, the approach allows a broader generalizability of the model as it incorporates the purposeful manipulation of perceptions based on established conceptualizations. To ensure sufficient treatment effects, we conducted a MANOVA. The analysis revealed significant group differences for perceived automation (F=266.69, p<.001) and user control (F=34.87, p<.001) due to positive effects of higher levels of the parameters on the participants’ perception of such.

Measures

We applied established scales and carefully adapted them to our research context to ensure content validity. To measure perceived user control, we relied on the construct by Chandran and Morwitz (2005). We adapted perceived automation from items applied by Schuetzler et al. (2014), Holtgraves et al. (2007) and Tallon and Kraemer (2007). To measure performance expectancy and behavioral intention to use we applied constructs from Venkatesh et al. (2003). To measure perceived risk, we adapted the overall risk construct applied by Featherman and Pavlou (2003) and to measure task complexity we used scales from...
Maynard and Hakel (1997). We translated all items into German and had them translated back into English twice to make sure they expressed what was originally intended.

**Data Collection and Sample**

Before commencing data collection, we pretested the vignettes as well as the survey with 19 experienced researchers to identify mistakes and ambiguities. Pre-testers were asked to think aloud during participation allowing us to identify even minor weaknesses in illustration and survey design. The main data collection took place in Q1 2019. The questionnaire was distributed via a mailing list composed of students from a large public German university and student groups in social networks. Samples primarily composed of students are frequently used in related studies (e.g. Polites and Karahanna 2012). To ensure sufficient engagement, we prohibited the participation with mobile devices. We incentivized participation with a lottery that awarded five online-shopping vouchers worth €30 each.

A total of 374 participants entered the questionnaire and 173 completed it. We discarded two participants, as they did not answer the two attention questions correctly. We screened the data for unengaged responses based on the standard deviation of Likert-scale responses, which did not lead to any exclusions. Of the remaining 171 participants, 60.8% were female and the average age was 26.6 years. 99.4% of the sample held at least a high school diploma, 67.8% were students. 65.2% of the participants that disclosed their income earned less than €1,500 per month (9.5% chose not to disclose).

**Results**

**Measurement Model**

Prior to the estimation of the structural model we evaluated the measurement model using a confirmatory factor analysis in SmartPLS 3 (Ringle et al. 2015). We calculated Cronbach’s alpha (CA) and composite reliability (CR) to represent internal consistency reliability of applied scales (Table 2). All constructs exceeded the threshold of 0.7 for CA and CR. Indicator reliability was implied by factor loadings above the threshold of 0.7 (Hair et al. 2011). All indicators fulfilled that criterion except for one in performance expectancy and one in perceived risk, which were excluded from the analysis. As all values for average variance extracted (AVE) were above the threshold of 0.5, convergent validity of the constructs was given.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Loadings</th>
<th>CA</th>
<th>CR</th>
<th>AVE</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Perceived automation</td>
<td>.782-.915</td>
<td>.899</td>
<td>.925</td>
<td>.755</td>
<td>.869</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Perceived user control</td>
<td>.703-.815</td>
<td>.788</td>
<td>.863</td>
<td>.612</td>
<td>.065</td>
<td>.782</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Performance expectancy</td>
<td>.707-.903</td>
<td>.780</td>
<td>.871</td>
<td>.695</td>
<td>.268</td>
<td>.352</td>
<td>.834</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) Perceived risk</td>
<td>.773-.924</td>
<td>.891</td>
<td>.920</td>
<td>.743</td>
<td>.019</td>
<td>-.207</td>
<td>-.349</td>
<td>.862</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Task complexity</td>
<td>.819-.892</td>
<td>.883</td>
<td>.919</td>
<td>.739</td>
<td>.025</td>
<td>.414</td>
<td>.058</td>
<td>.197</td>
<td>.860</td>
<td></td>
</tr>
<tr>
<td>(6) Intention to use</td>
<td>.969-.981</td>
<td>.974</td>
<td>.983</td>
<td>.950</td>
<td>-.133</td>
<td>.400</td>
<td>.709</td>
<td>-.351</td>
<td>.097</td>
<td>.975</td>
</tr>
</tbody>
</table>

Note: Elements in grey boxes represent the square root of AVE for the corresponding construct.

| Table 2. Factor Loadings, Internal Consistency Criteria, AVE, and Correlation Matrix |

To determine discriminant validity, we assessed indicator cross loadings, the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations. All factor loadings exceeded their cross loadings, the Fornell-Larcker criterion was met as the square roots of the AVEs exceeded the interconstruct correlations and all heterotrait-monotrait ratios were below the strictest threshold of 0.85 (Henseler et al. 2015). Therefore, we considered discriminant validity to be established.

**Structural Model**

Estimation results were obtained using partial least squares (PLS) structural equation modeling (SEM) and are displayed in Figure 2. To determine whether collinearity between the constructs was an issue in our analysis, we assessed the variance inflation factors (VIF) and found the highest value to be 1.204. Consequently, collinearity was not considered an issue. To test the significance of the path coefficients in our structural model, we conducted a bootstrapping procedure with 5000 subsamples.
The hypothesized positive effect of performance expectancy on the intention to use an investment management system (H1a) was found to be strong and significant. Furthermore, we found strong support for the hypothesized negative effect of perceived risk on the intention to use (H1b), while we could not support the effect of task complexity (H1c) in our data.

As hypothesized in H2, increased perceived automation had a strong and significant positive impact on the performance expectancy associated with a system. This indicates that algorithmic services are indeed considered superior in their ability to conduct complex tasks such as investment management. The hypothesized positive impact of perceived automation on the perception of risk (H3a) did not find support in our data. Although the effect is slightly positive, it was not found to be significant. With regards to perceived user control, path coefficients provided evidence for the hypothesized trade-off between a negative influence on perceived risk (H3b) and a positive influence on task complexity (H4). The relationships of perceived automation and user control with the perception of risk (H3a and H3b) indicated opposing effects of the parameters, though not significant. Variance in perceived automation and user control explained 7.2% of variance in performance expectancy, 4.4% of variance in perceived risk and 17.2% of variance in task complexity. Overall, performance expectancy, perceived risk and task complexity explained 52.5% of variance in intention to use.

![Figure 2. PLS Estimation Results (n=171, ***p<0.01, **p<0.05, *p<0.1)](image)

**Discussion**

In this study, we set out to investigate the considerations underlying the decision to use algorithmic instead of human decision support taking into account the role of control the user retains. Therefore, we proposed two trade-offs: One between increased performance expectancy due to the superiority of algorithmic conduct and increased perceived risk associated with higher levels of automation. The second trade-off considers the decreased perception of risk associated with higher levels of user control and a simultaneous increase in the perception of task complexity.

Support of hypotheses H1a and H2 indicates that individuals do indeed value algorithmic conduct in decision support. This is in line with the superiority of algorithms in financial decision-making and manifested in higher expected performance associated with automation (Harvey et al. 2017). Contrasting suggestions of prior studies, we do not find support for general user skepticism towards automated decision support (e.g. Diab et al. 2011). This suggests that in private investment decisions, user perceptions differ to previously investigated contexts. The structured nature of financial investment may explain greater appreciation of algorithmic conduct in investment management than in more intuitive tasks such as employee selection.

The absence of a significant effect of perceived automation on the perception of risk may be caused by the binary distinction of the parameter in the vignettes. Users might perceive the extremes of an entirely human and a solely algorithmic support as similarly risky. Intermediate levels of automation such as investment managers supported by algorithms may decrease the perception of risks by balancing weaknesses of the two extremes yielding a non-linear relationship between automation and risk. Particular attention must be paid to the conceptualization of risk when utilizing the context of robo-advisory. Ambiguity of the concept may arise as risk can be interpreted with respect to the system providing decision support as intended by our construct of perceived risk, though it may also be interpreted as a necessary component of a profitable investment portfolio or an attitude of investors and users of robo-advisors.
Furthermore, the results in support of hypotheses H3b and H1b show that perceived user control is associated with decreased perceived risk. This perception of less risk in systems with remaining user control may be explained by the concept of egocentric advice discounting (e.g. Yaniv and Kleinberger 2000), which states that users tend to rely more heavily on their own judgements and decisions. Further, this appreciation of control may arise due to irrationally high levels of user confidence, a behavioral bias widely evident in the context of financial investing, implying lower likelihoods to utilize financial advice (Calcagno and Monticone 2015). Algorithmic conduct in investment management may limit such cognitive biases apparent in investor behavior. Despite our finding of a significant positive effect of perceived user control on perceived task complexity, this increase does not significantly influence the intention to use. This may be explained by the fact that in this study the only alternative capital market participation to the use of an investment management service is self-management of investments. Although perceived user control of decision processes significantly raises perceived task complexity, it may not raise complexity to a level similar to self-management. Therefore, using the service with partial control, even though it is more complex than the investment with a fully autonomous service, may be perceived as far less complex than self-management, not leading to the expected decrease in the intention to use (H1c). However, in this study's design, the outside option was vital to ensure a realistic investment scenario for the participants.

Taking into account all model paths, we find evidence for positive impacts of higher levels of automation and user control on the usage intention of decision support in financial investing. While effects of increased perceived automation are mediated by an increase in performance expectancy, effects of increased user control are mediated by decreased perceived risk. In contrast, the model paths hypothesizing a negative impact of perceived automation and user control remained insignificant. Our results thus suggest a positive net effect of automation and user control on financial decision support.

Implications

This study offers theoretical as well as practical implications. We contribute to research on the interaction with consumer DSSs in general and the interaction with robo-advisors in particular. We add to theory by proposing the parameters of levels of automation and user control as drivers of decision support utilization and integrating the automation trade-off between expected performance and perceived risk as well as the trade-off in user control between perceived risk and task complexity. The empirical test of our model shows that the performance superiority of algorithms established in various tasks is indeed perceived and valued as such by users. Further, control over the system indirectly affects the usage intention due to its effect on perceived risk. Overall, our study enhances the understanding of user perceptions of automated decision support in private contexts as well as their valuation of control over decision processes.

Providers of systems supporting private decisions such as robo-advisors can benefit from the practical implications of our findings to system design. Increased perceived automation is likely to enhance the willingness to use a service. This should encourage providers to exploit the opportunities of automation. The perception of a possibility of control over the decisions in the form of approval or alteration also positively affects the usage intention by reducing the perceived risk. Providers may thus obtain users' confirmation of important steps during decision processes to enhance acceptability of their service.

Limitations and Future Research

Despite the careful design of this study, some limitations remain, posing avenues for further research on the topic. First, the use of a vignette may lead to more subtle observed effects than experiments employing prototypes or field data. Second, a larger and more representative sample of individual investors may further increase generalizability and explanatory power of our model including interaction effects between perceived automation and user control as well as larger measures of joint variance in parameters and mediators. Third, one difficulty in the design of our questionnaire was the need for applicability of the constructs to human and to algorithmic services. As most constructs are adapted from information systems literature, they were originally intended to measure the perception of a system such as a robo-advisor rather than a human service offering. Overall, the proposed model and the associated trade-offs form a promising foundation for further investigations of the interaction with consumer decision support. Researchers and practitioners should consider both the level of automation and user control as significant drivers of support utilization. A further distinction of the two parameter levels as well as large-scale experimental investigations of the relationships have the potential to further advance our understanding of the matter.
REFERENCES


