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Do investors walk their talk? Intention-behavior consistency of robo-advisor investors during stock market downturns

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Abstract: Robo-advisors, as computer-automated investment platforms following passive investment strategies, have gained a lot of popularity, customers, and assets under management in recent years. They offer accessible and affordable wealth management solutions to a wide customer base through low fees and minimum investment amounts while providing well-diversified portfolios at individually assessed risk profiles. This paper serves to examine the intention-behavior consistency of these investors related to stock market downturns in order to understand whether investors walk their talk and sell, hold, or buy when stock markets decline. By building on an interdisciplinary approach using both, the psychological theory of planned behavior and the economic theory of hyperbolic discounting, we highlight the role of investors' self-regulation. Through conducting a stepwise logistic regression on anonymized data of 10,000 customers of a Scandinavian robo-advisor as well as an out-of-sample prediction on a second data set, we find that many investors act inconsistently with their intentions during stock market downturns. Furthermore, results indicate that investors with intentions of inaction, investors of older age, investors who identify as female, and investors without sustainability preferences act more consistently. Lastly, we observe that the time between the onboarding and the stock market downturn does not have a clear effect on consistency. These results pose several implications regarding the design of robo-advisors and their investors' self-regulation.

Keywords: Investor behavior, robo-advisor, self-regulation, intention-behavior gap

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List of Abbreviations

AUC	Area under the receiver operating characteristic curve
CI	Confidence interval
DU	Discounted utility theory
ETF	Exchange-traded funds
EU	Expected utility theory
FPR	False positive rate
GDPR	General Data Protection Regulation
MiFID II	Markets and Financial Instruments Directive II
ROC	Receiver operating characteristic
S&P500	Standard & Poor's 500 index
Se	Sensitivity
Sp	Specificity
TPB	Theory of planned behavior
TPR	True positive rate
VIX	CBOE volatility index

1. Introduction

Nowadays, robo-advisors as computer-automated investment platforms are considered the most crucial disruption within the asset and wealth management industry, providing considerable diversity in digitalization and service delivery (Fan & Chatterjee, 2020; Phoon & Koh, 2018; Seiler & Fanenbruck, 2021). They capture significant market shares and are not only offered by fintech companies and startups but also by incumbent financial companies around the world trying to remain competitive, such as Deutsche Bank, Credit Suisse, Merryl Lynch, and Goldman Sachs (Beketov et al., 2018; D'Acunto et al., 2019; Phoon & Koh, 2018).

Concomitant with this development, a new generation of investors has emerged with digital preferences, financial interests, and the need for ongoing control over their investments and reliance on multiple sources of information (Beketov et al., 2018; Shanmuganathan, 2020). Robo-advisors offer financial decision aid, performance control, and transparency conveniently at any time, as they only require devices with internet access, such as smartphones or laptops, and often demand a low initial investment amount while charging low fees (Beketov et al., 2018; Brunen & Laubach, 2022). Therefore, they are widely advertised to retail customers, changing the paradox that investment services are primarily available to high-net-worth individuals (Beketov et al., 2018; Bhatia et al., 2022; Brunen & Laubach, 2022).

With the rising popularity of robo-advisors, research about robo-advisory services, their performance, and target customers has grown dramatically in recent years. Researchers suggest that robo-advisors may mitigate investors' behavioral biases as they help investors solve and understand complexities during the decision-making process through their user interfaces and architectural choices (Shanmuganathan, 2020; Tertilt & Scholz, 2018). However, robo-advisors transfer some degree of autonomy to investors that may result in suboptimal decisions, irrational behavior and behavioral biases (Bartlett & McCarley, 2019; Bhatia et al., 2020; D'Acunto et al., 2019). Hence, behavioral patterns of robo-advisor investors seem worth investigating.

This paper aims to shed light on robo-advisor investors' behavioral consistencies and inconsistencies regarding their pre-stated intentions in times of stock market downturns. Building on an interdisciplinary approach, by using both the psychological theory of planned behavior (TPB) and the economic theory of hyperbolic discounting to explicate the factors involved in decision-making, we highlight the role of self-control and myopia, and hence, self-regulation for the occurrence of intention-behavior gaps. By comparing investors' intentions with their actual behavior to either "buy stocks", "hold stocks", or "sell stocks", when stock markets decline by at least 10% within one month, we examine if robo-advisor investors "walk their talk", and act intention-behavior consistent. Further, this paper focuses on identifying patterns of intention-behavior consistency. More precisely, we investigate the influence of age, gender, intentions for inaction, the time between intention formation and behavior observation, and sustainability preferences on the intention-behavior relationship and relate inconsistencies of behavior to psychological concepts, such as self-regulatory failure.

The analysis is based on two data sets from a Scandinavian robo-advisory company, each including data from 10,000 randomly chosen customers during two stock market declines of at least 10% within one month. First, we conduct a stepwise logistic regression on the first data set to examine the intention-behavior gap and the influence of the different variables tested. To check the validity and generalizability of our model, we perform an out-of-sample prediction on the second data set covering a different stock market downturn and compare our predictions with the actual intention-behavior relationships.

We find that nearly every second investor acts inconsistently to their stated intention to either sell, hold, or buy during the first stock market downturn between 17.02.2020 and 13.03.2020. Additionally, we observe that investors with intentions of inaction, namely intentions to hold their portfolio, investors who are older, and investors who identify as female show higher intention-behavior consistency, which supports existing literature concerning self-regulation and the tested characteristics in other contexts. Besides, we identify that investors with sustainability preferences behave more inconsistently to their intentions. Further, we note that the time between intention formation and behavior observation, namely the period between the onboarding and the stock market downturn, does not show a clear influence on investors' consistency. By conducting an out-of-sample prediction on the second data set during a period in which the stock market declined by at least 10% within one month, from 12.09.2022 to 07.10.2022, we observe that our model correctly predicts 79.5% of the consistent investors and 41.6% of the inconsistent investors.

Since investors' intentions and actual behavior in periods of market downturns can have far-reaching impacts on their risk-profiling and chosen investment allocation between risky assets, we further aim to provide valuable implications of our analyses for the design of the robo-advisor we retrieved our data and its investors. By relating inconsistencies to self-regulatory failure, we provide suggestions for enhancing investors' intention-behavior consistency. Besides, we contribute to the existing literature about self-regulation and robo-advisor investors' behavior. Due to limitations that arose after adjusting the ideal framework because of lacking data availability, further research is needed to shed light on investors' intention-behavior consistency and also investigate the applicability of our findings to other robo-advisory companies.

The paper is structured in eight sections. The introductory section is followed by a chapter on the relevant literature about robo-advisory services and the theoretical background of the intention-behavior gap, comprising the psychological theory of planned behavior, the economic theory of hyperbolic discounting, and self-regulation. Section three describes the ideal framework, its constraints, and deviations of the ideal framework within this context and develops our hypotheses. While section four outlines the methodology, including the adapted framework and the underlying data as well as descriptive statistics, section five presents the findings, which are thoroughly discussed in section six, further including implications and limitations. Section seven draws relevant conclusions.

2. Background

To get a better understanding of our framework, the following section will cover the theoretical background for our analyses. First, robo-advisors, their services, their target customers, and connected potential behavioral biases will be introduced to highlight the specific context of our analyses. Afterward, we will inaugurate both the psychologic TPB as well as the economic theory of hyperbolic discounting to explicate the factors influencing the decision-making process. Self-regulation, or more precisely, self-control and myopia, will then be introduced as one cause for the occurrence of inconsistencies between intentions and actual behaviors.

2.1. Industrial background of robo-advisors as investment platforms

2.1.1. Emergence and characteristics of robo-advisors

In 2008, after the global financial crisis, the market environment was characterized by low-interest rates and deficient positive returns that gave rise to investors' demand for passive, automated, less expensive, and less risky investment opportunities (Fan & Chatterjee, 2020; Phoon & Koh, 2018). Hence, the first robo-advisors emerged in the post-crisis and combined artificial intelligence and quantitative models with few human interferences, mainly offering rebalancing services to automatically maintain a certain risk level (Bhatia et al., 2022; Phoon & Koh, 2018). Over the past 14 years, the technology and variety of these digital asset managers have advanced significantly; they have become more sophisticated, completely web-based, relying on artificial intelligence, and lacking any human interaction by traditional wealth managers (Beketov et al., 2018; Faloon & Scherer, 2017; Hildebrand & Bergner, 2021; Phoon & Koh, 2018; Shanmuganathan, 2020). Robo-advisors have also reached other areas of personal finance than investment advice, such as tax management, debt management, mortgage uptake, and lending (D'Acunto & Rossi, 2021). However, within this context, we will only focus on robo-advisors as automated investment platforms.

Today, robo-advisors as investment managers can be described as digital platforms offering customers computer-automated decision aid concerning asset and wealth management using algorithms and quantitative methods for automated portfolio management (Beketov et al., 2018; D'Acunto & Rossi, 2021; Phoon & Koh, 2018). They have gained popularity as they are considered more cost-efficient and affordable than traditional investment advice and offer access to diversified portfolios for various levels of risk sensitivity (Bartlett & McCarley, 2019;

Faloon & Scherer, 2017; Uhl & Rohner, 2018). Therefore, robo-advisors offer customization benefits by using data analytics techniques to center their design around the suitability of investment products to the individual customer, aiming to deliver the best match to the customers' risk tolerance, life, and financial circumstances (Phoon & Koh, 2018; Uhl & Rohner, 2018).

2.1.2. Business model and design of robo-advisors

Most robo-advisory companies, like the one we retrieved our data set from, operate in a similar workflow consisting of pre-selecting assets, identifying an investor's profile, including risk preferences and investment objectives, analyzing this information, and individually optimizing portfolio compositions, rebalancing, and performance monitoring as well as reporting.

Within the first steps of pre-selecting assets, robo-advisory companies focus on choosing various asset classes and types that are cost as well as risk-efficient and offer diversification benefits, mostly following passive investment strategies (Beketov et al., 2018; Bhatia et al., 2022; Faloon & Scherer, 2017; Uhl & Rohner, 2018). Thus, the asset universe of robo-advisory firms often consists of diversified exchange-traded funds (ETFs), yet some robo-advisory companies also select mutual funds, actively managed funds, or sustainable funds (Beketov et al., 2018; D'Acunto & Rossi, 2022; Faloon & Scherer, 2017).

As a second step, the robo-advisor collects information about their prospective customers grounded on web-based questionnaires regarding investment objectives, such as general or pension savings or the purchase of specific goods (Beketov et al., 2018; Faloon & Scherer, 2017). Moreover, the robo-advisor collects information about the customer to determine their risk capacity and economic suitability by asking questions about age, previous investment experience, anticipated investment horizon, and financial situation, such as net income, savings, debt, and current liquid assets (Bartlett & McCarley, 2019; Beketov et al., 2018), which is also the case in the onboarding questionnaire of the robo-advisor we have retrieved our data sets from. This process is often complemented by asking situational questions, such as whether investors are concerned with maximizing gains, minimizing losses, or both and whether they would sell or buy assets, or do nothing if their portfolio loses x% of value in a single month (Faloon & Scherer, 2017). Altogether, these questionnaires aim to understand the individual's risk tolerance and develop investor-specific risk profiles (Beketov et al., 2018; Bhatia et al., 2020). Further, within the European Union some of these questions are also required to comply with regulations. For instance, the Markets and Financial Instruments Directive II (MiFID II) requires robo-advisory companies to evaluate prospective customers' knowledge and experience, financial situation, and investment goals (European Parliament, 2014). Hence, the robo-advisor from whom we retrieved our data sets is legally obliged to ask questions regarding these factors.

After the information collection, the robo-advisor analyzes the data, resulting in a recommendation that offers a particular allocation between different asset classes and types for a customer-specific risk profile (Bartlett & McCarley, 2019; Shanmuganathan, 2020). The main components of the robo-advisor whose data we use, leading to the investors' recommendations, are the intended investment horizon, investment objective and answers to three risk-related questions. The specific underlying model used by the robo-advisor companies determines the degree of individualization it offers its customers and is usually kept highly confidential (D'Acunto et al., 2019; Faloon & Scherer, 2017). The portfolio optimization and asset allocation methods most frequently used are based upon the Modern Portfolio Theory approach by Markowitz 1952, the so-called mean-variance optimization, improved and augmented to some extent and sometimes complemented with other methods, such as Value at Risk optimization, Conditional Value at Risk optimization, Black-Littermann or Risk Parity (Beketov et al., 2018; D'Acunto et al., 2019; Shanmuganathan, 2020). Altogether, the complex programmed algorithm based on the chosen underlying financial models creates an investment recommendation for a customized portfolio for the investor, mainly comprising stocks and bonds (Fan & Chatterjee, 2020; Horn & Oehler, 2020). The depiction of the recommended allocation is often complemented by experience sampling, including a simulation of the chosen portfolio over time in good and bad market environments (Faloon & Scherer, 2017). These tools help the investor understand the risk-allocation of their investments, one of their most important financial decisions and shall result in persistent decisions as it enhances their subjective understanding of their risk decision (Kaufmann et al., 2013). The robo-advisor whose data sets we analyze recommends a particular portfolio allocation consisting of stocks and bonds and depicts its expected development by using experience sampling. It further allows the customer to deviate from the recommendation and to choose a different proportion of stocks and bonds within some boundaries, depending on the answers given in the onboarding, in order to adjust the riskiness of the portfolio. Thereby, the robo-advisor we retrieved the data from confers some degree of autonomy to investors, like other robo-advisors do as well (D'Acunto et al., 2019; Faloon & Scherer, 2017; Shanmuganathan, 2020).

After the investor has made their initial investment, the algorithm constantly monitors the portfolio (Beketov et al., 2018; Faloon & Scherer, 2017). By automatically rebalancing the portfolio, the robo-advisor keeps it at a certain threshold for maintaining the Value at Risk, risk level, portfolio structure, or asset allocation of the initially recommended portfolio (Beketov et al., 2018; Faloon & Scherer, 2017), which is also the case for the robo-advisor providing the data sets. Further, performance reviews and reports are made accessible through the robo-advisor companies' webpages, smartphone applications, or monthly e-mails, requiring little time and effort from customers (Beketov et al., 2018; Fan & Chatterjee, 2020). Within the European Union, MiFID II requires robo-advisory companies to immediately notify their customers when their portfolios have lost more than 10% of their values relative to the start of the quarter (European Parliament, 2014), which is also applicable to the robo-advisory company supplying the data. In addition, some robo-advisors, like the one we have retrieved our data, offer automatic deposit services (Fan & Chatterjee, 2020; Phoon & Koh, 2018).

2.1.3. Target customers of robo-advisors and their characteristics

Target customers of robo-advisors can be characterized by various factors, such as their net worth and income, age, gender, investment horizon, financial literacy, investment experience, education, expectations, fears, and sustainability preferences.

With respect to wealth and income, robo-advisors seem especially appealing to people with lower to middle-class net worth and income levels who might not meet the minimum investment amounts of traditional wealth management services (D'Hondt et al., 2020; D'Acunto & Rossi, 2022; Faloon & Scherer, 2017; Todd & Seay, 2020). Studies support this view by concluding that high-net-worth individuals, on average, only make up less than 10% of robo-advisors' customer base and that high-income individuals are less likely to adopt robo-advisors as investment platforms (D'Acunto et al., 2019; Fan & Chatterjee, 2020).

Regarding the age of investors, researchers agree that particularly younger people have been associated with using robo-advisors. Yet, the description of "younger" varies with different studies. For instance, this age group may include individuals between 18 and 35

(Woodyard & Grable, 2018), between 20 and 40 (Brenner & Meyll, 2020), or, more broadly, people under the age of 65 (Fan & Chatterjee, 2020). Since robo-advisors are web-based platforms, the target group of these services may be limited to individuals with some degree of technological literacy, and therefore, older investors with a lower degree of tech-savviness may be less likely to use robo-advisors (Beketov et al., 2018; Brenner & Meyll, 2020; Fan & Chatterjee, 2020). Concerning gender, studies revealed that female investors are more reluctant to use robo-advisors than their male counterparts (Brenner & Meyll, 2020; Brunen & Laubach, 2022; Seiler & Fanenbruck, 2021).

Additionally, regarding the investment horizon, most robo-advisor investors can be classified as investing long-term (Uhl & Rohner, 2018). With respect to financial literacy and investment experience, study results deviate. Some researchers found that people with a higher degree of financial literacy are more likely to use robo-advisors (Fan & Chatterjee, 2020; Woodyard & Grable, 2018), while others concluded that individuals with a lower degree of financial literacy tend to have a higher probability of using robo-advisors (Brenner & Meyll, 2020; Todd & Seay, 2020). Further, investors with various levels of previous investment experience seem to be attracted to robo-advisors (Brunen & Laubach, 2022). Regarding educational background, investors with various educational levels use robo-advisors, while people with a low educational background should be profiting the most (Brunen & Laubach, 2022; D'Hondt et al., 2020).

Furthermore, target customers can be characterized by their expectations of using robo-advisors. Robo-advisor adaptors actively search for financial advice, are concerned about the efficiency of their investment portfolio, and expect these services to perform better than they individually would on their own (Bartlett & McCarley, 2019; Horn & Oehler, 2020). Additionally, customers anticipate sophisticated and customized services and privacy (Beketov et al., 2018; Seiler & Fanenbruck, 2021). Moreover, the need to free up time and a perceived low level of difficulty have been stated as individuals' intentions for using robo-advisors (Fan & Chatterjee, 2020; Seiler & Fanenbruck, 2021). Besides, customers await constant accessibility, cost, and tax efficiency (Fan & Chatterjee, 2020). Individual investors who fear investment frauds are more likely to use robo-advisors since they eliminate potential conflicts of interest of human financial advisors associated with traditional asset and wealth management (Brenner & Meyll, 2020; Woodyard & Grable, 2018).

Altogether, by comparing users of robo-advisors with those of traditional financial advisors, who are often characterized as well-educated individuals who receive a high income, hold a significant part of their wealth in invested assets, have complex economies, and believe they possess a higher degree of financial knowledge (Uhl & Rohner, 2018; Woodyard & Grable, 2018), one can conclude that robo-advisors extent the customer base of traditional financial advisors by a much wider variety of individuals.

2.1.4. Robo-advisors and behavioral finance

Traditional finance theories, such as the efficient market hypothesis, assume that investors act rationally, aim to maximize their expected utility and update their beliefs when receiving new information, as described by Bayes' law (Barberis & Thaler, 2002; Fama, 1970; Hirshleifer, 2015). However, due to behavioral biases, individuals often do not act entirely rationally, fail to update their beliefs, or make choices that do not maximize their expected utility, leading to irrational investment decisions (Barberis & Thaler, 2002; Bhatia et al., 2022; Shanmuganathan, 2020). Nevertheless, investors can mitigate their behavioral biases by either preventing themselves from acting emotionally or finding an investment solution that inhibits them from acting emotionally (Uhl & Rohner, 2018).

In general, robo-advisors may be less biased than traditional human wealth managers, who might transfer behavioral biases to their customers while advising them (Bhatia et al., 2022; D'Acunto et al., 2019; D'Acunto & Rossi, 2021; Tao et al., 2021). Robo-advisors may even help mitigate investors' behavioral biases since they resolve complex issues that individuals cannot easily solve themselves, by using algorithms and help investors understand these solutions through their user interfaces and architectural designs (Shanmuganathan, 2020; Tertilt & Scholz, 2018). Active investors holding stocks directly face biases that lead to higher trading frequencies, lower expected utility, and poorer performance than passive investors who buy and hold a well-diversified portfolio (Barber & Odean, 2000; Grinblatt & Keloharju, 2009; Odean, 1998). Consequently, investors who follow passive investment strategies and buy and hold a well-diversified portfolio, as they do with robo-advisors, may not only have better investment results but also face fewer biases. This can be supported by a study conducted by Rossi (2020) revealing that the use of robo-advisors eliminated investors' home bias. Additionally, by rebalancing the portfolio to maintain strategic weights and a specific risk-return profile as well as providing countercyclical investing, robo-advisors may provide an investment solution and decision-making that inhibits investors from acting emotionally (D'Acunto et al., 2019; Shanmuganathan, 2020; Uhl & Rohner, 2018).

Nonetheless, robo-advisors may be subject to biases since the tool itself is developed by humans and may therefore encounter conflicts and limitations (D'Acunto et al., 2019; Rossi, 2020). As a consequence, decisions based on robo-advisors can be imperfect for various reasons. For instance, through incorrect judgments on the investment needs or inaccurate risk profiling by the algorithm (Bartlett & McCarley, 2019; Bhatia et al., 2020; Fan & Chatterjee, 2020). This can occur when robo-advisors fail to capture all relevant information about the customer's financial situation and psychological as well as attitudinal factors in the onboarding questionnaire (Fan & Chatterjee, 2020). Hence, if customers' risk profiles are assessed as more risk tolerant than they are, customers will get nervous when that risk materializes (Tertilt & Scholz, 2018).

Since robo-advisors transfer some degree of autonomy to investors, like the possibility of ignoring the robo-advisor's suggestion by changing the allocation, the occurrence of suboptimal investor choices, irrational behavior and behavioral biases cannot be completely eradicated (Bartlett & McCarley, 2019; Bhatia et al., 2020; D'Acunto et al., 2019).

2.2. Intention-behavior gap

As explained in the previous chapter, even though robo-advisors can be seen as a decision-aid for investors, the occurrence of biases and suboptimal investment decisions cannot be eradicated. Since this paper aims to assess robo-advisor investors' intention-behavior relationship, this chapter provides a short overview of the psychological TPB to elucidate the relationship between intentions and behaviors. Further, the economic theory of hyperbolic discounting will be discussed to illuminate investors' discrepancies in preferences. Ultimately, the theory of self-regulation, self-control, and myopia will be elaborated to highlight one cause for the intention-behavior gap.

2.2.1. Psychological view on the intention-behavior relationship

Explicating individuals' behavior in all its complexity can be a challenging task (Ajzen, 1991). The TPB delineates the proximal influences of an individual's decision to participate in a particular behavior, attempting to explain and predict human behavior in specific contexts

(Ajzen, 1991; Conner et al., 2000). Hence, this psychological theoretical framework tries to elucidate intention-behavior consistencies and inconsistencies (Sheeran, 2002).

The TPB comprises the idea that the performance of behavior depends conjointly on the intention to execute the behavior in question, perceived behavioral control, and their interactions with each other (Ajzen, 1991). Intentions reflect motivational aspects influencing behavior and indicate individuals' verdict to employ effort or a conscious plan to perform a behavior (Ajzen, 1991; Conner et al., 2000). A high degree of intention formation, referring to the extent to which individuals have assessed the consequences of their behavioral decisions, results in a higher predictive power of the actual behavior (Bagozzi & Yi, 1989; Sheeran, 2002), and is ascertained by favorable attitudes, subjective norms, and high perceived behavioral control (Conner et al., 2000). In turn, attitudes result spontaneously and constantly from beliefs accessible in memory, which can be affected by one's personality, education, age, gender, income, media exposure, and other sources of information (Ajzen, 2011).

Furthermore, perceived behavioral control can be described as an individual's perception of the degree to which the performance of a behavior is within one's own control or to what extent a behavior is seen as difficult or easy (Ajzen, 1991; Conner et al., 2000). The perception of these characteristics that are facilitating or inhibiting the performance of behavior can be specified as control beliefs (Conner & Armitage, 1998). These beliefs comprise internal control factors, such as personal deficiencies, emotions, attitudes, abilities, knowledge, and information, but also external control factors, such as opportunities, barriers, availabilities, cooperation, unexpected situations, dependencies on other individuals and resources (Conner & Armitage, 1998; Sheeran, 2002). Since control beliefs can change when internal or external control factors change, perceived behavioral control may vary with time and with the situation (Ajzen, 1991; Conner & Armitage, 1998; Sheeran, 2002). For instance, in times of economic crises, individuals' beliefs in a sense of control decline (Bu et al., 2020).

The theory specifies that for the accurate prediction of behavior, the specified context must be the same for intention, perceived behavioral control, and the performed behavior (Ajzen, 1991). Additionally, intention and perceived behavioral control need to remain persistent, and perceived behavioral control should realistically portray actual control (Ajzen, 1991). Discrepancies between the expressed willingness to perform a behavior and the actual behavior exist, as people fail to behave according to their stated intentions (Sheeran, 2002), which can be explained by self-regulatory failure (Ajzen, 2011), and more precisely, self-control failure and misregulation (Baumeister & Heatherton, 1996).

2.2.2. Economic decisions in risky and dynamic environments

Despite the psychological theory, it is important to understand how investors evaluate alternatives and make decisions from an economic perspective. Within economics, the expected utility theory (EU) and the discounted utility theory (DU) represent similarly structured models in which decision-makers select between alternatives founded on a weighted sum of utilities (Prelec & Loewenstein, 1991). Within EU, the discount weights represent risks, while within DU, they represent time delays (Prelec & Loewenstein, 1991). Nevertheless, time and uncertainty are interlinked attributes (Prelec & Loewenstein, 1991), and therefore, investors in our analyses meet two peculiarities that build an interesting setting for analyzing intention-behavior inconsistencies.

DU allows the comparison and the quantification of preferences over consumption profiles by incorporating them in an intertemporal utility function (Frederick et al., 2002; Samuelson, 1937). The key assumption of this model represents the possibility of condensing all choice considerations into a single discount rate (Frederick et al., 2002; Samuelson, 1937). Hence, time delays show the same impact on decision-makers choices irrespective of the time of occurrence (Prelec & Loewenstein, 1991). Contrarily, EU represents a descriptive model of decision-making under uncertainty (Tversky & Kahneman, 1992) and assumes that only relative probabilities matter to the decision-maker (Prelec & Loewenstein, 1991).

Both of the traditional financial theories assume that decision-makers fully integrate new alternatives about their planned consumption (DU) or existing wealth (EU) into their decisions (Barberis & Thaler, 2002; Fama, 1970; Hirshleifer, 2015; Machina, 1989; Prelec & Loewenstein, 1991). However, this assumption does not hold in reality as decision-makers separate new alternatives from current wealth or future consumption, leading to several similar anomalies of both theories (Machina, 1989; Prelec & Loewenstein, 1991), which are relevant in the context of our analyses.

One anomaly within DU is represented by the common difference effect implying that in reality the influence of constant time differences between two delayed outputs becomes increasingly less pronounced, leading to time-varying discount rates, which result in dynamically inconsistent behavior (Loewenstein, George & Prelec, 1992; Thaler, Richard, 1981). The corresponding anomaly in EU is represented by the common ratio effect, and therefore, preferences sensitive to ratios and differences along a dimension are reflected in neither of the theories (Prelec & Loewenstein, 1991). Another effect that is not reflected by DU, but often observed empirically is the gain/loss asymmetry, implying that losses are discounted at a lower rate than gains (Loewenstein & Prelec, 1992; Thaler, 1981). In EU, there exists a corresponding reflection effect, as preferences shift from risk aversion to risk seeking when positive gambles are mirrored by turning all payoffs negative (Hershey & Schoemaker, 1980; Kahneman & Tversky, 1979). Hence, neither in EU nor DU, losses are treated differently than gains, nevertheless observed in reality (Prelec & Loewenstein, 1991). Further, the absolute magnitude effect in DU specifies that, large outcomes are discounted less than small outcomes (Benzion et al., 1989; Loewenstein & Prelec, 1992; Thaler, 1981). A similar effect occurs in the EU, as risk seeking for small gains develops to risk aversion with increasing volume, and risk aversion for very small losses to risk seeking with rising volume (Markowitz, 1952; Prelec & Loewenstein, 1991). Another anomaly is represented by the framing effect**,** the delay speed-up effect in DU, and the so-called isolation effect in EU, implying inconsistent preferences when the same alternative is presented differently (Kahneman & Tversky, 1979; Loewenstein, G., 1988; Prelec & Loewenstein, 1991).

As a result of these shortcomings of DU and EU, several theoretical models have emerged to resolve these anomalies, such as prospect theory and hyperbolic discounting models (Frederick et al., 2002; Kahneman & Tversky, 1979; Laibson, 1997). Since the latter explains dynamic inconsistencies between decision-makers' preferences at different points in time, the use of hyperbolic discounting models seems applicable in our context.

Hyperbolic discounting models aim to explicate the discrepancies between individuals' preferences today and preferences held in the future by using hyperbolic discount functions, which are characterized by high discount rates in the short-term and low discount rates in the long-term (Laibson, 1997). These declining discount rates result in dynamically inconsistent preferences (Laibson, 1994). What might seem like the optimal approach from an individual's perspective today is not the optimal choice from the individual's future perspective (Laibson, 1994). For instance, given the low discount rate in the long-term, it may require low effort for an individual to state today that he is going to quit an undesired habit in one year (Laibson, 1994). However, when the next year actually arises, the individual is faced with the high short-term discount rate that changes his preference not to quit the undesired habit now and instead he decides to postpone the required sacrifice another year into the future (Laibson, 1994). Diminishing discount rates over time and the resulting discrepancies in individuals' preferences may be explained by self-control failure and impatience (Akerlof, 1991; Benzion et al., 1989; Laibson, 1997). However, there is another rationale for the observed empirical findings that intertemporal decisions are associated with diminishing sensitivity as utils become more distant in time (Laibson & Gabaix, 2017). Even perfectly patient agents without time preferences can be characterized by a hyperbolic discount model when accounting for individuals' imperfect foresight or myopia (Laibson & Gabaix, 2017). Capital markets, in particular, are afflicted by mostly unforeseeable shocks with unpredictable implications. For instance, investors might be aware of the likelihood of an economic recession in the near future but underestimate its impact. Their misperception leads these investors to believe they will act in a certain way, when in reality, at the time the recession occurs and stock markets decline to a greater extent than originally anticipated, they will behave differently than initially intended. In this case, the underlying reason for investors' intention-behavior gap did not arise because the impact was in the "future", i.e. because of procrastination and laziness, but rather from the miss-assessment of the impact of the crisis (Laibson & Gabaix, 2017). Laibson and Gabaix (2017) find that individuals who experience less forecasting noise and, therefore, inhibit lower discounting rates are either more intelligent, more experienced in the respective domain, or older with more life experience. Consequently, these groups of individuals are more likely to display consistency between their intentions and actual behaviors.

2.2.3. Self-regulation failure

As discussed in the economic and psychological theories, low self-control and myopia, which can be summarized as self-regulation failure, can cause the observation of intention-behavior discrepancies. Since self-regulation represents a complex and versatile process, it is impossible to determine a single cause or causal order that explicates the instances of self-regulatory failure, which ultimately explains steady, long-term individual differences in intention-behavior consistencies (Baumeister & Heatherton, 1996). For instance, self-regulation failure can be caused by uncertainty, stress, fatigue, inner disagreements, negative self-states, anxiety, or distress, inhibiting individuals from acting as they intended since these factors deplete one's strength (Baumeister & Heatherton, 1996; Gollwitzer, 1999). Conceptually, within the field of self-regulation, a distinction is made between the concepts of underregulation, or so-called self-control failure, and misregulation, namely myopia.

Self-control failure arises as individuals lack clear, consistent, stable standards or as they fail to monitor their activities (Baumeister & Heatherton, 1996; Thaler, Richard H. & Shefrin, 1981; Uhr et al., 2021). Hence, self-control failure occurs when individuals are aware of the harmful consequences of specific behaviors but, nevertheless, miss the strength and willpower to overrule impulses they wish to control (Baumeister & Heatherton, 1996; Uhr et al., 2021). Individuals may fail to act according to their intentions if they forget those and neglect to perform the intended behavior, which can be caused by demanding conditions, interruptions, or lack of attention (East, 1993; Einstein et al., 2003). Within the field of finance, a lack of attention is negatively related to investment performance, especially in uncertain environments (Gargano & Rossi, 2018). Individuals losing attentional control fail to consider long-term consequences and implications and instead base their decisions on short-term results (Baumeister & Heatherton, 1996; de Ridder et al., 2012). Hence, investors with low degrees of self-control will prefer an immediate payoff over an increased future payoff and hence, yield into an immediate desire at a future cost, ultimately resulting in low degrees of welfare (O'Donoghue & Rabin, 1999). People with a low degree of self-control are more likely to give in to impulses, encounter second thoughts when the situation arises, and fail to regulate their emotions and control their thoughts (de Ridder et al., 2012; Gollwitzer & Sheeran, 2006) and hence, they tend to be more exposed to adverse events, like financial shocks (Gathergood, 2012). Overall, an individual's level of self-control can vary across situations and time (de Ridder et al., 2012). Researchers assume that behaviors that are not automated and more effortful require a higher degree of self-control than automatic behaviors (de Ridder et al., 2012). The lack of self-control can also be displayed by procrastination, leading individuals to postpone actions to another day without anticipating that they will postpone again when that day comes (Akerlof, 1991; O'Donoghue & Rabin, 1999).

Besides, misregulation or myopia implies that individuals act based on false suppositions about themselves, the world and the future (Baumeister & Heatherton, 1996). The beliefs individuals have can be incomplete and inaccurate, relying on irrational premises, biased by self-serving incentives, anger, fear, or other emotions, and therefore, may fail to reflect reality (Ajzen, 2011). Hence, wrong assumptions about the future may result in investors' lack of perfect foresight and therefore cause discrepancies in individuals' preferences (Laibson & Gabaix, 2017). Individuals fail to anticipate that their preferences will change in the future and may even fail to recognize when their preferences have changed (Akerlof, 1991). For instance, investors may not have anticipated liquidity constraints caused by other influential factors during a stock market downturn and therefore deviate from their preference of buying stocks due to a lack of investable liquid assets which they have not foreseen.

To mitigate self-regulatory failure, individuals may enhance their pre-commitment (Laibson, 1997) if they are aware of their dynamic inconsistencies between preferences (Heimer et al., 2021; Strotz, 1955). Hence, commitment mechanisms can be observed in a variety of different forms and domains, from investing in a pension plan without the possibility of withdrawing prior to the payout date to getting a long-term gym membership (DellaVigna & Malmendier, 2006; Laibson, 1997). While binding commitments do not offer opportunities for deviations, soft commitments can be reviewed ex-post and, therefore, may be an "illusion of commitment" (Heimer et al., 2021). Within this context, the asked questions in the onboarding of European robo-advisors due to MiFID II regulations may constitute an "illusion of commitment" as investors are asked prior to their investments, about their intended future investment behaviors under certain circumstances, such as a stock market downturn and therefore commit to a strategy with a possible revision later on. In a similar context, Heimer et al. (2021) have shown that non-binding commitments caused by MiFID II counterproductively resulted in investors' increased risk-taking and deviations from previously set non-binding strategies (Heimer et al., 2021). Therefore, within this context, it seems unclear whether these forms of soft commitments enhance or worsen investors' self-regulation.

3. Framework & Hypotheses

The primary objective of this paper is to investigate whether robo-advisor investors act consistently with their stated intentions to either deposit money, do nothing, or withdraw money from their robo-advisor account when the value of the stocks they hold with the robo-advisor decreases by 10% within one month and to determine whether some specified variables have a significant influence on the intention-behavior relationship. In the following, we will first introduce our ideal framework based on the psychological TPB to assess intention-behavior consistencies and inconsistencies and draw inconsistencies back to self-regulatory failure and, therefore, declining discount rates as depicted in hyperbolic discounting models that we previously discussed. Then, we will describe the constraints occurring within our context, leading to deviations from the ideal framework. Moreover, we will develop the hypotheses. Within the following, the termination "robo-advisor", "robo-advisory company", and "robo-advisor accounts" refer to the same robo-advisor we have retrieved our data set.

3.1. Ideal framework

3.1.1. Holistic overview of investors' financial situation

In general, investors' investment behavior should be analyzed on an aggregate basis, considering all their investments, instead of single investments on an isolated basis, like the purchase or sale of a stock. Hence, one should examine investors' net worth comprising their financial wealth, such as investments in stocks and bonds and investments in real estate less the owed liabilities (Mian et al., 2013). This equation can be depicted as follows:

$$NW_t = S_t + B_t + H_t - D_t \tag{1}$$

where:

NW_t : net worth in period t

S_t : market value of stocks in period t

B_t : market value of bonds in period t

H_t : market value of housing in period t

D_t : market value of owed debt in period t

As these variables constitute factors of an investor's household's balance sheet, additional variables may also be taken into consideration, as all areas of a household's balance sheets are interlinked and should, therefore, not be assessed in isolation (D'Acunto & Rossi, 2022). For instance, a global, unexpected health crisis, such as the covid-19 pandemic, increased the likelihood of liquidity constraints for households (Li et al., 2020). In such a context, budgetary adjustments for individual items of a household's net worth, such as a sale of stocks, may be considered suboptimal when assessed in isolation. However, by taking all other household balance sheet items into account, the sale of stocks may be the optimal choice. A household experiencing liquidity constraints may use the liquidity retrieved from the sale of stocks to fulfill its mortgage obligations to ameliorate its solvency situation. Hence, in an ideal setting, we would assess an investor on a holistic basis by evaluating all factors on their household's balance sheet, such as human capital, mortgage loans, durable goods, and stock investments.

3.1.2. Context

For analyzing the intention-behavior gap, the context for intention, the perceived behavioral control, and the performed behavior should be the same (Ajzen, 1991), implying that all three factors can be observed and measured. This appraisal can be conducted directly by asking questions about individuals' intentions and capacities to perform a behavior, or indirectly, e.g., by inquiring them about their beliefs and ability to manage specific impeding or facilitating factors. Therefore, in an ideal setting, we would measure investors' intentions regarding the following context: "If you have invested in stocks and your portfolio value declines by 10% within one month, how would you adjust your personal household balance sheet?" Further, we would evaluate investors' perceived behavioral control to approximate the actual control with questions regarding whether they perceive the behavior of adjusting their household balance sheet when the value of their stocks they hold declines by 10% within one month as within their control and whether they see the performance of this behavior as difficult or easy. Ultimately, we would investigate their actual behavior by observing their actions when the situation occurs and the value of the stocks they hold declines by 10% within one month.

3.1.3. Temporal stability and actual control

Additionally, the intentions and perceived behavioral control need to remain persistent in the period between the framing of intention and the observation of behavior to ensure the predictive validity of intention on behavior (Ajzen, 1991). Therefore, within our context, no unforeseen events should occur, or new information should become available that may change investors' intentions and perceived behavioral control, resulting in changes in the adjustment of their personal household balance sheets. To account for that, we would need to know and manage precisely which events occur and which information becomes available to the investors that have an impact on investors' households' balance sheets, whether they have accounted for them at the time of stating their preferences, and whether and to which degree they could impact pre-formed intentions and perceived behavioral control, and ultimately the actual behavior of each individual investor.

Additionally, for the accurate prediction of behavior, investors' perceived behavioral control should realistically portray actual control (Ajzen, 1991). This implies that in an ideal setting, we need to ensure that all investors in our data sample do not over- nor underestimate the control they believe they possess about performing the intended adjustment of their household balance sheet.

3.2. Constraints and deviations from the ideal framework

Due to a lack of data availability and observability, we face several constraints that result in deviations from the ideal framework which are explained in the following.

3.2.1. Robo-advisory investors' intentions

To draw conclusions on investors' intention-behavior consistency and inconsistency, we define the answers to the following question investors get asked in the onboarding questionnaire of the robo-advisor which provided both our data sets as an approximation for investors' intentions.

"The value of stocks can go up and down. Let us assume that you have invested in stocks, and their value decreases by 10% within one month. What do you do?"[1]

a. *Sell stocks*
b. *Hold stocks*
c. *Buy stocks*

[1] *Original in Swedish:*
"Värdet på aktier kan gå upp och ned. Vi antar att du har investerat i aktier och värdet på dina aktier minskar med 10 % under en månad. Vad gör du? a. säljer aktier; b. behåller aktier; c.köper aktier

Due to MiFID II regulations, the robo-advisor company must understand and ensure that its customers comprehend the riskiness of their investments, and therefore, prospective customers need to answer this question with one of the three provided answer suggestions. The answers to the question are also used, among other factors, to determine the customized recommended allocation between stocks and bonds. Hence, we possess data on the intention of all investors from our data set. We believe that the question formulation in our framework is representative of measuring intentions as it corresponds to typical implementation intentions, such as, if an individual experiences situation X, they will perform behavior Y (Brandstätter et al., 2001; Gollwitzer, 1999). However, the question only asks about stock investments in general. As explained earlier, the robo-advisor account may not be the only brokerage account through which investors make investments into financial assets. Since we do not possess information on their stock investments beyond their robo-advisor account, we have to make the following subtle but crucial adjustment to the interpretation of the considered onboarding question that investigates investors' intentions:

"The value of the stocks you hold in your portfolio with the robo-advisor decreases by 10% within one month. What do you do?"

a. *Withdraw money from my account*
b. *Neither withdraw nor deposit money from/to my account*
c. *Deposit more money to my account*

Similarly, we also slightly adapt the answer options as outlined above. Investors with the original response "sell stocks" are proxied to withdraw money from their robo-advisor account, investors with the answer "hold stocks" neither withdraw nor deposit money to their robo-advisor account, and investors with the answer "buy stocks" deposit money to their robo-advisor account. Since withdrawals or deposits of money are related to the robo-advisor selling or buying funds that, in turn, are invested in stocks or bonds or both, we argue that this proxy is a sufficient representation of investors' intentions. As data points about the portfolio allocation of stocks and bonds for each individual investor are available, investors who only hold bonds will be excluded.

3.2.2. Perceived behavioral control and self-regulatory capacity

Within this context, perceived behavioral control would also be adjusted in line with the intention. Therefore, perceived behavioral control would reflect investors' perception of the degree to which depositing money to their robo-advisor accounts, withdrawing money from their robo-advisor accounts, or neither withdrawing money from nor depositing money to their accounts is seen as within their own control and or sensed as difficult or easy. Since we do not obtain data that can measure or approximate the perceived behavioral control of each investor directly or indirectly, we do not account for this factor in our model. Hence, due to the lack of data availability, we can also not ensure that perceived behavioral control matches the actual control.

3.2.3. Robo-advisor investors' actual behavior

As elaborated in the ideal framework, to draw conclusions on the decision-making of investors we would need complete oversight of investors' household balance sheets. Hence we would need, among others, collectively exhaustive information on their financial and real estate assets as well as their debt obligations. However, we only possess data on their stock and bond investments with one robo-advisor, which is a critical limitation. In our analyses, we are unable not only to consider investors' real estate assets and liabilities but also to include possible additional stock and bond investments with other brokerages. Consequently, this paper cannot evaluate normatively whether investors are making the right or wrong decision by adjusting their robo-advisor investments and analyzes inconsistencies between their stated intentions and actions only. Following thereinafter, when mentioning actual behavior, we only refer to investors' actions in their robo-advisor accounts of our data sets.

The actual behavior can have three different expressions. First, investors can withdraw money from their robo-advisor accounts and hence, sell stocks indirectly. Second, investors neither withdraw money from their robo-advisor accounts nor deposit money to their robo-advisor accounts and, therefore, do nothing. Third, investors can deposit money into their robo-advisor accounts and, thus, buy stocks indirectly.

Since investors may deposit and withdraw money several times during the observation period, we focus on the accumulation of deposits and withdrawals. Hence, for the assessment of these three behaviors, we take the accumulated deposits and accumulated withdrawals of each individual investor over a specified period and adjust them by their usual amount of the pre-determined monthly savings plans, as they distort the accumulated deposits. Monthly savings plans are an offering of the robo-advisor who provided the data sets, which can be characterized as automatic recurring deposits. Each investor can choose to set up a monthly savings plan with an individually specified amount, which will be deducted automatically from their bank account on an individually set day each month. Investors are also able to adjust both the amount and day and are also able to skip certain months or cancel the automatic monthly savings plan entirely. Therefore, an investor's actual behavior is inferred from the following equation:

$$Actual\ behavior_t = D_{acc,t} - S_{t-1} - W_{acc,t} \tag{2}$$

where:
$D_{acc,t}$: accumulated deposits in period t
S_{t-1} : amount of savings plan in period t-1
$W_{acc,t}$: accumulated withdrawals in period t

By subtracting the usual amount of the savings plan of the period prior to the observation period from the accumulated deposits in the observation period, we retrieve the actively made deposits by investors in the observation period. Hence, in this step, we not only capture actively made one-time deposits but also adjustments made to the savings plan. Then, by further deducting the accumulated withdrawals made in the observation period, we obtain the direction of the actual behavior in the observation period. *Appendix 1* depicts all possible scenarios. The outcome of equation (2) can be interpreted in the following way.

A "sell stocks" behavior is given by:

$$D_{acc,t} - S_{t-1} - W_{acc,t} < 0 \tag{3}$$

Hence, an investor without a monthly savings plan will be allocated to the "sell stocks" behavior if their accumulated withdrawals exceed the accumulated deposits in the observation period. Additionally, an investor with a monthly savings plan without withdrawals and accumulated deposits smaller than the amount of the monthly savings plan that was set in the month prior to the observation period would also be categorized as a "sell stocks" behavior, implicating that the investor actively reduced the amount of the savings plan, paused, or canceled the plan entirely. All further scenarios are depicted in *Appendix 1*.

A "hold stocks" behavior is given by:

$$D_{acc,t} - S_{t-1} - W_{acc,t} = 0 \quad (4)$$

This situation arises if an investor without a monthly savings plan has deposited and withdrawn the same accumulated amount within the observation period. Additionally, an investor with a monthly savings plan who did not actively make any deposits and withdrawals within one period would be categorized into a "hold stocks" behavior if the amount of accumulated deposits equals the amount of the monthly savings plan that was set in the month prior to the observation period. All further scenarios are delineated in *Appendix 1*.

A "buy stocks" behavior is given by:

$$D_{acc,t} - S_{t-1} - W_{acc,t} > 0 \quad (5)$$

An investor without a monthly savings plan is assigned to this category if they have deposited a higher amount than withdrawn on an accumulated basis within the observation period. Besides, an investor with a monthly savings plan without withdrawals would be categorized into a "buy stocks" behavior if the amount of accumulated deposits would exceed the amount of the monthly savings plan that was set in the month prior to the observation period since it implies they actively increased their savings plan or made one-time deposits additionally to the savings plan. All further scenarios are visualized in *Appendix 1*.

3.2.4. Observation period

Since the context of the actual behavior should match the context of the intention, we need to observe the investors' behavior when the value of their stocks in their robo-advisor account declines by 10% in one month. However, our data set does not allow for tracking each individual investor's account value. Therefore, we use the development of the Standard & Poor's 500 index (S&P500) as a proxy for the account values of all investors since the S&P500 is generally known as an adequate benchmark for overall stock market performance (Cremers et al., 2013), and the robo-advisor investors in our data set indirectly hold stocks in their diversified portfolios. As described previously, robo-advisor investors with a 100% bond allocation will not be considered in our analyses. Based on the data available, the two periods of 17.02.2020 to 13.03.2020 and 12.09.2022 to 07.10.2022 represent the right context for the observation of the intended behavior, as the S&P500 declined by more than 10% in both periods.

In the first period, from 17.02.2020 to 13.03.2020, the S&P500 lost approximately 19.5% (Yahoo Finance, 2022). The overall market uncertainty over that timeframe is reflected in the CBOE volatility index (VIX), which provides a benchmark of expected short-term market volatility (Whaley, 2009) The VIX increased by 286% in this period, indicating a high level of uncertainty (Yahoo Finance, 2022). The development of both the S&P500 and the VIX during this time is visualized in *Appendix 2*. Based on the significant drop of the S&P500 and the uncertainty in the market, it is highly likely that the funds the robo-advisory companies invest their customers' money in and consequently, the customers' stock portions of their portfolios lost at least 10% of their value respectively. Therefore, we believe it is highly likely that the situation of the intended behavior has occurred.

In the second period, from 12.09.2022 to 07.10.2022, the S&P500 lost approximately 10.9% (Yahoo Finance, 2022), clearing the hurdle of a 10% stock market downturn as visualized in *Appendix 3*. During this period, the VIX increased by 29%, indicating a slightly increased level of uncertainty in the market (Yahoo Finance, 2022). Besides, it should be noted though that this market downturn is significantly less pronounced than the first one from 17.02.2020 to 13.03.2020, potentially limiting its comparability and applicability. We will further elaborate on this issue later on.

The observation points of investors' behavior in our analyses are extended to a four-week period for several reasons. First, the onboarding question directly refers to a one-month period, yet it does not specify the exact period when the action should be observed, e.g., at the beginning, middle, or end of the specified month. Additionally, investors in our data set have the possibility of implementing monthly savings plans, implying that an individually pre-defined amount of money will be deposited automatically on an individually pre-specified day each month. To account for these automatic deposits and not mistakenly evaluate them as a different behavior, we need to observe a four-week period.

3.3. Hypotheses

In this chapter, we will develop six hypotheses based on a combination of the previously introduced economic theory of hyperbolic discounting and the psychological TPB, indicating that self-regulation, and therefore, self-control and myopia, play a significant role for intention-behavior inconsistencies.

For several reasons, we suggest that investors do not act according to their pre-stated intentions in our context and expect to observe intention-behavior gaps of investors in our first data set during a period shaped by the emergence of covid-19, a global, unexpected health crisis. We propose that investors were affected by self-regulatory failure during the stock market downturn, inhibiting them from acting as they intended. Since the covid-19 pandemic has generated high volatility and uncertainty in global financial markets, it has affected investors' emotions negatively (Kuhnen & Knutson, 2011; Talwar et al., 2021) and led to a rise of fear, diminishing their sense of control and overall confidence in their decision-making process (Bu et al., 2020; Cohn et al., 2015; Kuhnen & Knutson, 2011). Therefore, increased uncertainty, stress, and anxiety may have caused investors' self-control failure and, thus, self-regulatory failure, which led to emotional, impulsive behavior and ultimately to deviations from pre-stated intentions. Additionally, we suggest that investors may not have fully considered the nature and context of a stock market downturn when forming their intention. As suggested by Gabaix and Laibson (2017), even individuals with a high degree of self-control do not possess perfect foresight over potential future crises, and therefore, false estimations of the overall crisis impact, such as unanticipated liquidity constraints and influences on other items of their household balance sheet, could have also led to the observation of discrepancies. Moreover, the previously described "illusion of commitment" could have encouraged investors to take on more risks due to the possibility of revising their initial decisions, which subsequently might result in inconsistencies between planned and actual behavior once that risk materialized. Hence, we suggest:

Hypothesis 1. Investors act inconsistently with their intentions.

Further, we theorize that investors who intended to "hold stocks" will act more consistently than investors who opted for "sell stocks" or "buy stocks". Selling and buying represent active behaviors, and investors require more effort to log into their robo-advisor accounts, enter an amount to withdraw or deposit, or adjust or cancel their monthly savings plans and confirm their actions. Passively holding a portfolio or continuing a savings plan and, therefore, do nothing requires little effort and can be seen as an automatic behavior. Since individuals need to show a higher level of self-control to perform a behavior requiring more effort, promoting impulsive behavior (Conner et al., 2000; Hepler et al., 2012), and automatic behaviors require less self-control and have a higher likelihood of implementation (de Ridder et al., 2012; Sheeran et al., 2003), we suggest the following:

Hypothesis 2. Investors with an intention to "hold stocks" act more consistently than investors with intentions to "buy stocks" or "sell stocks".

Moreover, we propose that demographic factors can also have an influence on intention-behavior consistency. More precisely, we hypothesize that older investors should behave more consistently than their younger counterparts, as they experience less forecasting noise and, therefore, less self-regulatory failure, as they have more life experience and consequently better forecasting skills, and exhibit lower discounting (Laibson & Gabaix, 2017). In our context, older individuals may have gained investing experience during previous stock market downturns, such as the financial crisis of 2008. Additionally, since attention in investment contexts increases with age (Gargano & Rossi, 2018), older investors may not lose attentional control easily and therefore do not fail to consider the long-term consequences of their actions. Several studies have shown in various contexts that an individual's self-regulatory ability increases with age, resulting in less self-control failure (Bettschart et al., 2021; de Ridder et al., 2012; Hennecke & Freund, 2010; Hofmann et al., 2012) and that individuals get more skilled in developing and formulating personal goals, concentrating on them, and selecting fewer conflicting goals with increasing age (Freund et al., 2009; Riediger & Freund, 2006). Therefore, we derive:

Hypothesis 3. Intention-behavior consistency increases with age.

In addition, we suggest that women show higher intention-behavior consistency than men. Several studies in various contexts suggest that females possess higher self-regulatory capacities and a greater ability to regulate attention and impulses (Bjorklund & Kipp, 1996; Cross et al., 2011; Else-Quest et al., 2006; Hosseini-Kamkar & Morton, 2014; Steel, 2007). Since self-regulatory failure relates to higher intention-behavior inconsistency, we suggest that it may be more difficult for males to act upon their pre-formed intentions than for their female counterparts. From this argumentation, it follows that:

Hypothesis 4. Female investors act more consistently than male investors.

Furthermore, we suggest that the temporal distance plays a role in intention-behavior consistency since increasing temporal distance makes it more difficult for individuals to anticipate and account for all factors when forming their intentions (Salisbury & Feinberg, 2008). As news about covid-19 had already arisen in December 2019, investors opening an account after that point in time should have been more likely to take this news into account when forming their intentions, compared to investors who have been investing with the robo-advisor before that time and have a higher probability of imperfect foresight. Additionally, investors with a greater period between onboarding and the stock market downturn face low discount rates in the long-term, and it may require little effort to state their intentions during the onboarding. However, when the stock market downturn occurs, these investors are faced with high short-term discount rates that change their preferences. Hence, we hypothesize:

Hypothesis 5. Investors with a shorter period between onboarding and the stock market downturn show higher intention-behavior consistency.

Besides, we hypothesize that investors with sustainability preferences act more consistent than investors without. Research has shown that future-oriented individuals display a higher intention-behavior consistency (Ittersum, 2012). Since individuals fail to perceive any instant, personal benefits from sustainable choices, they envision future societal-level benefits (Farmer et al., 2017). As sustainable-aware robo-advisor investors choose sustainable investment options (Brunen & Laubach, 2022), we suggest they can be seen as future-oriented. Additionally, self-control represents an important antecedent of sustainability preferences and evidence suggests a robust relationship between both variables (Nguyen et al., 2019). These findings further suggest that investors with sustainability preferences should possess more self-control and show higher intention-behavior consistency. From this argumentation, it follows that:

Hypothesis 6. Investors with sustainability preferences act more consistently than investors without.

4. Methodology

Altogether, the constraints mentioned before require adaptations to the ideal framework. To test the validity and generalizability of our analyses, we conduct an out-of-sample prediction on a second data set in another period of a stock market decline. The adapted framework, the out-of-sample prediction, and the descriptive statistics of both data sets used for the analyses will be elaborated in the following.

4.1. Adapted framework

We derive investors' intentions and actual behavior as described in the previous chapters and then match both for each individual investor. Consistency occurs if the intention and the actual behavior match, while in all other instances, intention-behavior inconsistency applies. Thus, there are 9 possible combinations of intention and actual behavior, summarized in *Appendix 4*. It is worth mentioning, that we do not investigate the absolute values of the withdrawals and deposits made within investors' robo-advisor accounts, as these cannot be adequately compared across investors, given that their income and wealth levels vary and are provided subjectively without external validation. Additionally, since the desirability and undesirability of intentions, behavior, and the resulting welfare consequences are highly influenced by non-normative contextual, individual factors (de Ridder et al., 2012; Heimer et al., 2021) and as we do not have insights into investors' household balance sheets, we will focus solely on the appearance of consistencies and inconsistencies between their intended behavior and actual behavior within their robo-advisor account, without any further judgment of desirability of an investor's actions.

For our analyses, we will run a set of stepwise logistic regressions. Beginning with the simplest regression of predicting the consistency (CONS) based on investors' intention (INT), we incrementally add the additional factors of age (AGE), gender (GEND), the time between intention and actual behavior, in our analyses, the time between the onboarding and the start date of the decline of the S&P500 index by at least 10% (TIME) in one month, and sustainability preferences (SUST). We set up our final regression model as follows:

$$CONS_i = a + \beta_1 * INT_i + \beta_2 * AGE_i + \beta_3 * GEND_i + \beta_4 * TIME_i + \beta_5 * SUST_i + \varepsilon \quad (6)$$

By comparing the five different regression models based on their Akaike information criterion (AIC) values, we ensure that our final model is the most suitable for our data set.

4.2. Out-of-sample prediction

To test the validity and generalizability of our model, we will use it to predict the intention-behavior consistencies and inconsistencies of another group of randomly chosen investors, during another period in which the S&P500 index declined by at least 10%, namely from 12.09.2022 to 07.10.2022. For each investor in our second data set, we will estimate the probability of consistency based on our original regression model (6). Next, we will define a threshold probability value that will allow us to binary divide all investors in intention-behavior consistent and inconsistent, which subsequently will be compared to the actual consistency of these investors. By examining the receiver operating characteristic (ROC) curve, a visual representation of the trade-off between the true positive rate (TPR, sensitivity) and the false positive rate (FPR, 1 – specificity) for each possible threshold value, we optimize the threshold probability value such that we make the fewest false predictions (Parikh et al., 2008). Furthermore, we will evaluate the area under the ROC curve (AUC) which can be interpreted as the probability that a random consistent investor is ranked before a random inconsistent investor, allowing us to assess the overall performance of our prediction (Flach et al., 2011).

4.3. Descriptive Statistics of the first data set

4.3.1. General overview

Our first data set, directly obtained from a Scandinavian robo-advisor, provides anonymized data from randomly selected 10,000 investors. By adjusting for investors holding no stocks and for investors missing some data points, our first data set comprises information on 9,964 investors with a tax residency in Sweden. All investors use the robo-advisor as part of their personal investments and had set up their account before 17.02.2020. Due to General Data Protection Regulation (GDPR), certain data points were anonymized by providing data ranges instead of exact values. These binned data include age, the time between the onboarding to the robo-advisor and stock market downturn, accumulated deposits, accumulated withdrawals, and the amount of automatic monthly savings plan as of the month prior to the observation period.

For the regressions, we solve the issue of binned data points by using the middle of the bin as a proxy for the actual values. We do not estimate exact values for the bins of accumulated deposits, accumulated withdrawals, and the amount of the monthly savings plans as the indication of the actual behavior may be distorted, leading to misclassifications of intention-behavior consistency as the different data points would be estimated independently from each other. Hence, investors' monthly savings plans would no longer exactly match their accumulated deposits in the observation period even though investors neither adjusted their monthly savings plans nor actively made any deposits. Therefore, they would be wrongly allocated to “sell stocks” or “buy stocks” instead of “hold stocks" behavior. Since the bin gradation for the age data (5 years) and time between the onboarding and the stock market downturn (10 days) is relatively small, the impact on the regression outcome by applying an appropriate distribution to estimate exact values would be negligible. Consequently, we decided not to apply a suitable distribution, such as a normal or Poisson distribution, and instead use the middle of each bin, even though the data points will then be concentrated.

4.3.2. Investors’ characteristics of the first data set

Table 1 summarizes the descriptive statistics on the investors of our first data sample. The investors are divided into 3,893 (39%) individuals identifying as female and 6,071 (61%) identifying as male, which supports existing research stating that men are more likely to use robo-advisors than women. Moreover, the investors' ages range from 18[2] to 85 years, with an average (median) age of 41 (36) years, which is also in line with existing literature. Additionally, the average (median) self-reported monthly net income at the time of the onboarding corresponds to 30,846 SEK (27,500 SEK), and 50% of our first sample’s investors earn between 22,500 SEK and 37,500 SEK monthly. This supports existing literature stating that typical target customers of robo-advisors receive middle-class income. With respect to the time between the intention statement and the observation of actual behavior, the average (median) number of days between signing up for the robo-advisor and 17.02.2020 is 282 (210), which is around 11.05.2019 (22.07.2019). The oldest account in our first data sample was set up 1,180 days before 17.02.2020. Furthermore, 205 investors have set up an account just within ten days prior to the reference date.

[2] While *Table 1* states the age of 22 as minimum age, representing the middle of the lowest age group bin, it is highly likely that the youngest investor is 18 years old, corresponding to the lower bound of this age bin.

As described previously, the robo-advisor proposes a customized allocation between stock and bond funds for each investor with the option for manual adjustments. On average (median), investors allocate 76% (80%) to stocks and 24% (20%) to bonds. Additionally, investors must decide between two investment options, a broad, highly diversified portfolio and a portfolio with a focus on social and environmental responsibility. In the following, we will refer to investors who have chosen the latter as investors with sustainability preferences. In our first data set, 2,156 (22%) investors have sustainability preferences, while 7,808 (78%) have not and hence, invested in the broad, highly diversified fund. It should be noted that the investment option focusing on social and environmental responsibility has been offered to customers since mid-November 2019.

Table 1: Overview of investors' characteristics of the first data set

This table contains the descriptive statistics of the 9,964 investors in our first data set. These include gender distribution (top left), sustainability preference (bottom left) and age, monthly income, the number of days between the onboarding to the robo-advisor and the stock market downturn (time), and the stock and bond allocation (right). It should be noted that the descriptive statistics of age, monthly net income, and time are calculated based on bins following our previous reasoning, and hence, the distribution might be skewed.

Gender distribution in sample	#	%
Female	3893	39%
Male	6071	61%
Total number of investors	**9964**	**100%**

Sustainability preference in sample	#	%
Yes	2156	22%
No	7808	78%
Total number of investors	**9964**	**100%**

	Mean	Std Dev	Min	25th	Median	75th	Max
Age	41	9,7	22	22	36	38	85
Monthly net income (SEK)	30846	15.608,4	2500	22500	27500	37500	112500
Time (# of days)	282	254,1	0	80	210	370	1180
Stock allocation	76%	0,2	10%	60%	80%	100%	100%
Bond allocation	24%	0,2	0%	0%	20%	40%	90%

4.3.3. Investors' intentions of the first data set

By examining the onboarding question used to approximate the intention, we conclude that 397 (4%) investors stated they would withdraw money, 6,838 (69%) investors would neither withdraw money nor deposit money, and 2,729 (27%) investors would deposit money to their robo-advisor account (*Appendix 5*). The observation that 96% of the investors in the data set intend to either "hold" or "buy" is in line with existing literature stating that robo-advisor investors are investing long-term.

4.3.4. Investors' actual behavior of the first data set

The actual behavior is derived by deducting the accumulated withdrawals in the observation period and the amount of the automatic monthly savings plan in the month prior to the observation period from the accumulated deposits in the observation period, from 17.02.2020 to 13.03.2020. As displayed in *Table 2*, automatic monthly savings plans have been implemented by 6,585 (66%) investors, with an average (median) monthly automatic deposit amount of 3,832 SEK (500 SEK). This overall average is highly inflated by 24 investors with a monthly savings amount of more than 100,000 SEK. The remaining 3,379 (34%) investors have decided not to deposit money automatically to their robo-advisor accounts.

Altogether, the average (median) accumulated deposit amounts to 10,482 SEK (4,000 SEK), as depicted in *Table 2*. Since a small group of investors has deposited large amounts of money, up to 1,000,000 SEK, the median is significantly lower than the average. *Table 2* shows that even though the number of investors withdrawing money is considerably lower than of investors depositing money, the average (median) withdrawal is noticeably higher, at 83,826 SEK (22,500 SEK). Again, the median is significantly lower than the average, due to six investors who had withdrawn up to 1,000,000 SEK from their robo-advisor accounts.

Table 2: Activities of investors

This table lists the descriptive statistics of the savings plans that were in place the month prior to 17.02.2020 and the actual deposits and withdrawals within our observation period from 17.02.2020 to 13.03.2020. It should be noted that the deposit, withdrawal, and savings plan statistics are calculated based on bins following our previous reasoning, potentially skewing the distribution.

Actual Behavior	Mean	Std Dev	Min	25th	Median	75th	Max	#	%
Deposits (SEK)	10482	75789	500	2000	4000	12500	1000000	7374	74%
Withdrawals (SEK)	83826	155940	500	7500	22500	95000	1000000	743	7%
Savings plan (SEK)	3832	18769	500	500	500	2500	850000	6585	66%

We can observe six different behaviors of the 3,379 (34%) investors without a monthly savings plan, as depicted in *Table 3*. Out of these investors, 262 (3%) are categorized into the “sell stocks” behavior since 188 (2%) investors have withdrawn money without making deposits, and 74 (1%) investors have withdrawn money but deposited a smaller amount. Further, 2,092 (21%) of the investors without a savings plan can be allocated to the “hold stocks” behavior. 2,078 (21%) have neither made deposits nor withdrawals, while 14 (0.1%) investors have deposited the exact same amount they withdrew in the observation period. The behavior of the remaining 1,025 (10%) investors without savings plans can be categorized as “buy stocks” behavior. 1,013 (10%) investors only deposited money without making withdrawals, whereas 12 (0.1%) investors have also withdrawn money but deposited a higher amount in the observation period.

Table 3: Actual behavior scenarios of investors without a monthly savings plan

This table allocates all investors without a savings plan in the month prior to 17.02.2020 into activity scenarios, specifies the respective required conditions, sorts them into "sell stocks", "hold stocks" and "buy stocks" behavior categories and gives a qualitative description of each scenario.

No savings plan

#	Deposits	Withdrawals	Behavior (formula)	Relation of variables	Actual behavior	# investors	%	Description
1	D = 0	W = 0	D - W = 0	D = W	Hold	2078	20.9%	*No action*
2	D > 0	W = 0	D - W > 0	D > W	Buy	1013	10.2%	*Only deposited*
3	D = 0	W > 0	D - W < 0	D < W	Sell	188	1.9%	*Only withdrawn*
4	D > 0	W > 0	D - W < 0	D < W	Sell	74	0.7%	*Deposited, but withdrawn more*
5	D > 0	W > 0	D - W = 0	D = W	Hold	14	0.1%	*Deposited and withdrawn same amount*
6	D > 0	W > 0	D - W > 0	D > W	Buy	12	0.1%	*Withdrawn, but deposited more*

In addition, we notice ten different behaviors in the group of 6,585 (66%) investors with a monthly savings plan, summarized in *Table 4*. 886 (9%) investors can be allocated to the "sell stocks" behavior, which can be further divided into six different categories. 263 (3%) investors have not made any deposits, indicating a pause or cancellation of the savings plan, but also have not withdrawn any money from their robo-advisor accounts during the observation period. Another 236 (2%) investors have deposited the same amount as their monthly savings plan prior to the observation period, indicating a continuation of the savings plan, yet, they have withdrawn money during that time. Furthermore, 187 (2%) investors have deposited a lower amount than the amount of the monthly savings plan prior to the observation period, indicating a negative adjustment of the monthly savings plan, without making any withdrawals. Moreover, 113 (1%) of all investors have deposited a higher amount than the amount of their monthly savings plans prior to the observation period but nevertheless, have withdrawn more money from their account than deposited on an accumulated basis. Additionally, 61 (0.6%) investors have not made any deposits, implying a cancellation or pause of their monthly savings plans, and further have withdrawn money from their accounts. Ultimately, 26 (0.3%) investors that can be allocated in the "sell stocks" category, have made deposits that are smaller than the amount of the monthly savings plan prior to the observation period, indicating an adjustment of the monthly savings plan and additionally have withdrawn money from their accounts. Besides, the behavior of 4,183 (42%) investors can be classified as "hold stocks" behavior who have deposited the exact same amount as the amount of the monthly savings plan prior to the observation period, indicating a continuation of the original savings plan, without withdrawing any money. Of course, investors in this category could have also canceled, paused, or reduced their monthly savings plans and topped the difference manually by actively making one-time deposits. However, we believe that this scenario is rather less likely and therefore suggest that all investors in the category have not made any active changes to their savings plan. A further scenario that would bring investors into the "hold stocks" category would be the withdrawal of the exact amount investors have deposited in excess of the amounts of their savings plans. Yet, we did not observe any investors within this category. Moreover, the behavior of the remaining 1,516 (15%) investors can be allocated into the "buy stocks" category. Out of these investors, 1,497 (15%) have deposited a higher amount than the amount of the monthly savings plan prior to the observation period without making any withdrawals. This observation indicates that investors have either increased the amount of their monthly savings plans or have made additional one-time deposits in excess of their savings plan, or reduced their monthly savings plans and made one-time deposits resulting in an amount exceeding the amount of the monthly savings plan prior to the observation period. Ultimately, 19 (0.2%) investors have deposited a higher amount than the amount of the monthly savings plan prior to the observation period and have withdrawn an amount smaller than the accumulated deposits.

Table 4: Actual behavior scenarios of investors with a monthly savings plan

This table allocates all investors with a savings plan as of the month prior to 17.02.2020 into activity scenarios, specifies the respective required conditions, sorts them into "sell stocks", "hold stocks" and "buy stocks" actual behavior categories, and gives a qualitative description of each scenario.

Savings plan in place

#	Deposits	Withdrawals	Behavior (formula)	Relation of variables	Actual behavior	# investors	%	Description
7	D > 0	W = 0	D - W - S = 0	D = S	Hold	4183	42,0%	*Deposited same amount as original savings plan, no withdrawals*
8	D > 0	W = 0	D - W - S > 0	D > S	Buy	1497	15,0%	*Deposited higher amount than orginal savings plan, no withdrawals*
9	D = 0	W = 0	D - W - S < 0	D < S	Sell	263	2,6%	*Original savings plan paused or canceled, no further deposits or withdrawals*
10	D > 0	W > 0	D - W - S < 0	D = S	Sell	236	2,4%	*Deposited same amount as original savings plan, further withdrawals*
11	D > 0	W = 0	D - W - S < 0	D < S	Sell	187	1,9%	*Deposited lower amount than original savings plan, no withdrawals*
12	D > 0	W > 0	D - W - S < 0	D > S; D - S < W	Sell	113	1,1%	*Deposited higher amount than original savings plan, withdrawn higher amount than excess deposits*
13	D = 0	W > 0	D - W - S < 0	D < W	Sell	61	0,6%	*Original savings plan paused or canceled, no further deposits but withdrawals*
14	D > 0	W > 0	D - W - S < 0	D < S	Sell	26	0,3%	*Deposited lower amount than original savings plan, further withdrawals*
15	D > 0	W > 0	D - W - S > 0	D > S; D - S > W	Buy	19	0,2%	*Deposited higher amount than original savings plan, withdrawn lower amount than excess deposits*
16	D > 0	W > 0	D - W - S = 0	D > S; D - S = W	Hold	0	0,0%	*Deposited higher amount than original savings plan, withdrawn same amount as excess deposits*

Overall, we can classify 1,148 (12%) investors into the "sell stocks" behavior, 6,275 (63%) into the "hold stocks" behavior, and 2,541 (26%) into the "buy stocks" behavior, as summarized in *Appendix 6*.

4.4. Descriptive statistics of the second data set

4.4.1. General overview

Our second data set was directly provided by the same robo-advisor as the first data set and includes anonymized data from randomly selected 10,000 investors using the robo-advisor as part of their personal investments with accounts created before 12.09.2022. After adapting for investors with 100% bond portfolios and investors with missing data points, our second data set encompasses data from 9,970 investors. Again, for GDPR reasons, the same data points as in the first data set were anonymized by providing ranges instead of exact values.

4.4.2. Investor characteristics of the second data set

Table 5 summarizes the descriptive statistics on the investors of our second data set. These can be segregated into 4,528 (45%) individuals who identify as female and 5,442 (55%) who identify as male. Furthermore, the investors' ages are distributed similarly as in the first data set, ranging from 18[3] to 85, with an average (median) age of 41 (38). However, half of the investors are aged between 33 and 48, differing from the first one with 50% of the investors aged between 22 and 38 years. In addition, the average (median) self-reported monthly net income at the time of the onboarding corresponds to 30,860 SEK (27,500 SEK), and 50% of our second sample's investors earn between 22,500 SEK and 37,500 SEK monthly, similar to the first data set. Moreover, the average (median) number of days between the onboarding and 12.09.2022 is 683 (600), with the oldest account created 2,080 days before 12.09.2022. Additionally, 24 investors have set up an account within ten days prior to the reference date.

Besides, investors in the second data set, very similar to the ones in the first data set, allocate on average (median) 80% (80%) to stocks and 20% (20%) to bonds. Further, 3,577 (36%) investors have a sustainability preference, whereas 6,393 (64%) have not, and therefore, invested in the broad, highly diversified fund only. This distribution deviates from the first data set, in which only 22% of all investors have sustainability preferences.

Table 5: Overview of investors' characteristics of the second data set

This table contains the descriptive statistics of the 9,970 investors in our second data set. These include gender distribution (top left), sustainability preference (bottom left) and age, monthly income, the number of days between the onboarding to the robo-advisor and the stock market downturn (time), and the stock and bond allocation (right). It should be noted that the descriptive statistics of age, monthly net income, and time are calculated based on bins following our previous reasoning, and hence, the distribution might be skewed.

Gender distribution in sample	#	%
Female	4528	45%
Male	5442	55%
Total number of investors	**9970**	**100%**

Sustainability preference in sample	#	%
Yes	3577	36%
No	6393	64%
Total number of investors	**9970**	**100%**

	Mean	Std Dev	Min	25th	Median	75th	Max
Age	41	13,3	22	33	38	48	85
Monthly net income (SEK)	30860	14215,8	2500	22500	27500	37500	112500
Time (# of days)	683	419,5	0	350	600	960	2080
Stock allocation	80%	0,2	10%	70%	80%	100%	100%
Bond allocation	20%	0,2	0%	0%	20%	30%	90%

[3] While *Table 5* states the age of 22 as minimum age, representing the middle of the lowest age group bin, it is highly likely that the youngest investor is 18 years old, corresponding to the lower bound of this age bin.

5. Findings

Our findings are structured in the following way. First, we present the results of our logistic regression for the first data set, followed by the outcomes of the out-of-sample prediction from the thereby derived model on the second data set.

5.1. Intention-behavior consistency

Investors' intention-behavior consistency and inconsistency of our first data set are depicted in *Table 6*. The illustration shows investors who acted consistently to their pre-stated intentions on the top-to-bottom diagonal of the table and investors who behaved inconsistently outside of this diagonal. Thus, out of the sample's 9,964 investors, 5,207 (52%) have acted consistently, while 4,757 (48%) investors have behaved inconsistently with their pre-stated intentions.

Table 6: Intention and actual behavior matrix of the first data sample

This contingency table sorts all investors into the nine possible intention-behavior combinations. The three highlighted green boxes on the top-to-bottom diagonal represent consistent investors, while the other six combinations depict inconsistent investors. The percentages in parentheses depict the share of investors within each intention category that fall into a sell, hold or buy actual behavior, respectively, and add up to 100% for each row.

		Actual Behavior		
		Sell	**Hold**	**Buy**
Intention	**Sell**	76 (19%)	246 (62%)	75 (19%)
	Hold	769 (11%)	4,367 (64%)	1,702 (25%)
	Buy	303 (11%)	1,662 (61%)	764 (28%)

Based on the related literature and the availability of data points, we have identified five variables that may influence the consistency of individual investors, namely intention (INT), age (AGE), gender (GEN), the time between the onboarding to the robo-advisor and the market downturn (TIME) and sustainability preference (SUST). Beginning with a logistic regression only considering the intention as an independent variable, we systematically add the other variables until we get our final regression model, whose results are presented in *Table 7*. The results of the other 4 models are depicted *Appendix 7*. The here shown decline of the AIC values indicates that our final model is the best fit for our data.

Table 7: Logistic regression results of the final model

*We investigate the influence of the variables INT, AGE, GEND (female/male), TIME, and SUST (not present/present) on the consistency of robo-advisor investors, as discussed in the hypotheses. This table presents the logistic regression output. The p-values associated with the z-value of each variable are shown in parentheses. *, **, and ***, indicate statistical significance at the 5%, 1% and 0.1% level, respectively.*

	Dependent variable:
	CONS
INTSELL	-2.054***
	(<0.001)
INTBUY	-1.509***
	(<0.001)
AGE	0.0038*
	(0.021)
GEND	-0.126**
	(0.005)
TIME	0.0002*
	(0.021)
SUST	-0.1627**
	(0.002)
Constant	0.469***
	(<0.001)
Observations	9,964
Log Likelihood	-6,270.2
Akaike Inf. Crit.	12,554.4

Altogether, we uncover that all five variables in question influence intention-behavior consistency in a statistically significant way. To facilitate the interpretation of the regression results, we interpret the associated odds ratios that are summarized in *Appendix 8*. First, we can observe that investors with intentions to "sell stocks" or "buy stocks" act less consistently than investors with intentions to "hold stocks", statistically significant at the 0.1% level. The odds ratio of the "sell stocks" intention amounts to 0.1282 (95% confidence interval (CI): 0.0986 – 0.1647), implying that the odds of behaving consistently are 87.18% less likely for investors with intentions to "sell stocks" than for investors with intentions to "hold stocks". Similarly, the odds ratio of investors with intentions to "buy stocks" equals 0.2211 (95% CI: 0.2003 – 0.2438), insinuating the chances of behaving consistently are increased by 77.89% for investors with intentions to "hold stocks" than for investors with intentions to "buy stocks". These differences are also depicted in *Table 8*. Hence, of the 6,838 investors with intentions to "hold stocks", 4,367 (64%) have acted consistently to their pre-stated intentions, while only 2,471 (36%) behaved inconsistently. On the contrary, only 19% of the investors with intentions to "sell stocks" and 28% of those with intentions to "buy stocks" have shown consistent behavior.

Table 8: Intention-behavior consistency and intention relationship

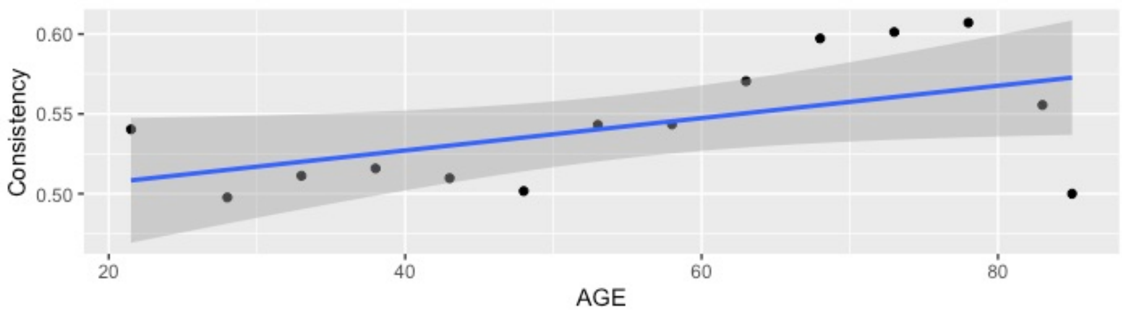
This table depicts the number and share of intention-behavior consistent and inconsistent investors grouped by their pre-stated intentions to "sell", "hold", or "buy" stocks. The percentages in parentheses depict the share of investors within each intention category who behaved consistently or inconsistently, and add up to 100% for each row.

		Intention-behavior	
		Consistent	**Inconsistent**
Intention	**Sell**	76 (19%)	321 (81%)
	Hold	4,367 (64%)	2,471 (36%)
	Buy	764 (28%)	1,965 (72%)

Second, we reveal that AGE has a statistically significant impact at the 5% level on CONS, suggesting higher intention-behavior consistency for increasing ages. The odds ratio of the variable age is 1.0038 (95% CI: 1.0006 – 1.0071), implying that for every single year rise in age, the odds to display consistency increase by 0.38%. The relationship between age and intention-behavior consistency can also be observed in *Figure 1*. Generally, we observe that with an increase in age the probability of acting consistently increases up to the age of 78 years. The sudden drop around the 78-year age mark should be considered with caution, as the group of investors older than 78 only comprises 28 (0.3%) individuals, influencing the shape of the dotted graph. Accounting for these outliers, overall, the positive effect of age on consistency discovered in the logistic regression model prevails in *Figure 1*.

Figure 1: Intention-behavior consistency and age relationship

This figure visualizes the relationship between investors' age and their intention-behavior consistency. Each dot represents an age bin and the respective percentage of consistent investors within this bin. It is worth mentioning that the number of investors per bin significantly varies. Thus, for some age bins, the number of investors might be too low to be representative.



Third, we find that GEND has a statistically significant influence on CONS at the 1% level, indicating that investors identifying as male act less consistently than their female counterparts. The odds ratio for male investors is 0.8816 (95% CI: 0.8074 – 0.9626), suggesting that the odds of males exhibiting intention-behavior consistency is 11.84% lower than that of females. As displayed in *Table 9*, of 3,893 investors who identify as female, 2,196 (56%) behaved consistently, while only 3,011 (50%) of 6,071 investors identifying as male showed behavior in line with their pre-stated intentions.

Table 9: Intention-behavior consistency and gender relationship

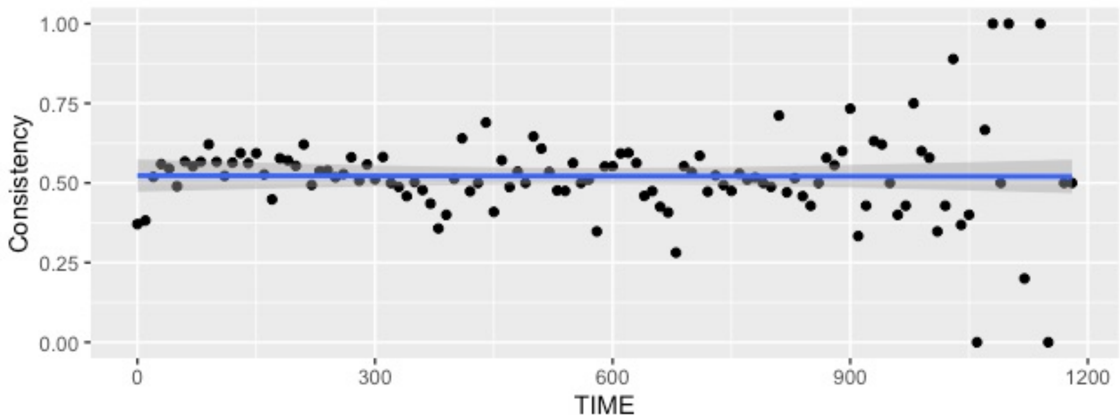
This table depicts the number and share of intention-behavior consistent and inconsistent investors grouped by the gender of investors. The percentages in parentheses depict the share of investors identifying as male or female who behaved consistently or inconsistently, and add up to 100% for each row.

		Intention-behavior	
		Consistent	**Inconsistent**
Gender	**Male**	3,011 (50%)	3,060 (50%)
	Female	2,196 (56%)	1,697 (44%)

Fourth, in our logistic regression, we observe a slightly positive effect of TIME on CONS, statistically significant at the 5% level. This result indicates that investors with a longer period between the onboarding to the robo-advisor and the stock market downturn, or the statement of intention and observation of actual behavior, show a higher intention-behavior consistency. The odds ratio at 1.0002 (95% CI: 1.00003 – 1.00037) connotes that one additional day between the onboarding and the market downturn increases the likelihood of acting consistently by 0.02%. For further illustration, we depict the relationship between the number of days between the onboarding and the stock market downturn and the intention-behavior consistency in *Figure 2*. In this visualization, we conclude that even though the logistic regression suggests a slightly positive effect of TIME on CONS, there seems to be no clear relationship between the period between the onboarding to the robo-advisor and the stock market downturn and, therefore, the time between intention formation and behavior observation, and intention-behavior consistency.

Figure 2: Intention-behavior consistency and time relationship

This figure visualizes the relationship of investors' time between the onboarding to the robo-advisor and the stock market downturn and their intention-behavior consistency. Each dot presents a time bin and the respective percentage of consistent investors within this bin. It is worth mentioning that the number of investors per bin significantly varies. Thus, for some time bins, the number of investors might be too low to be representative.



Finally, we find that SUST shows a statistically negative effect at the 1% level on CONS, entailing that investors with sustainability preferences behave less consistently than those without. The odds ratio of sustainability preferences is 0.8498 (95% CI: 0.7659 – 0.9429), implying that the odds for acting consistently with pre-stated intentions are reduced by 15.02% for investors with sustainability preferences than for those without. Out of the 2,156 investors with sustainability preferences, 1,095 (51%) have behaved consistently with their pre-stated intention, while 1,061 (49%) acted inconsistently, as exhibited in *Table 10*. Conversely, out of the 7,808 investors with a broad portfolio, 4,112 (53%) have shown intention-behavior consistency, whereas 3,696 (47%) have not.

Table 10: Intention-behavior consistency and sustainability preference relationship

This table depicts the number and share of intention-behavior consistent and inconsistent investors grouped by the existence of sustainability preferences. The percentages in parentheses depict the share of investors with or without sustainability preferences who behaved consistently or inconsistently, and add up to 100% for each row.

		Intention-behavior	
		Consistent	**Inconsistent**
Sustaina-bility preference	**Yes**	1,095 (51%)	1,061 (49%)
	No	4112 (53%)	3696 (47%)

5.2. Out-of-sample prediction

To test the validity and generalizability of our findings, we predict the probabilities for intention-behavior consistency and inconsistency for a second data set during a month in which the S&P500 index decreased by 10%, namely in the period from 12.09.2022 to 07.10.2022, and compare our predictions with the actual intention-behavior consistency and inconsistency of investors during this second observation period. Applying our final regression model (*Table 7*) to the new data sample, we receive a probability estimate for each investor to display consistent or inconsistent behavior with pre-stated intentions. The distribution of the estimated probabilities is depicted in *Appendix 9*.

In the first step, we chose a probability of 50% as our threshold value for behaving consistently. In other words, we classify each investor with a predicted probability equal to or higher than 50% as intention-behavior consistent. As displayed in *Table 11*, in this case, we correctly identify 4,348 (80%) of the total 5,466 consistent investors as consistent while, falsely classifying the remaining 1,118 (20%). For the inconsistent investors, we are only able to correctly identify 1,875 (42%) of the total 4,504 intention-behavior inconsistent investors as inconsistent while we falsely classify 2,629 (58%) investors. In total, we can correctly sort 6,223 (62%) investors into their respective consistency groups, whereas for 3,747 (38%) investors we make the wrong prediction.

Table 11: Comparison of predicted and actual consistency

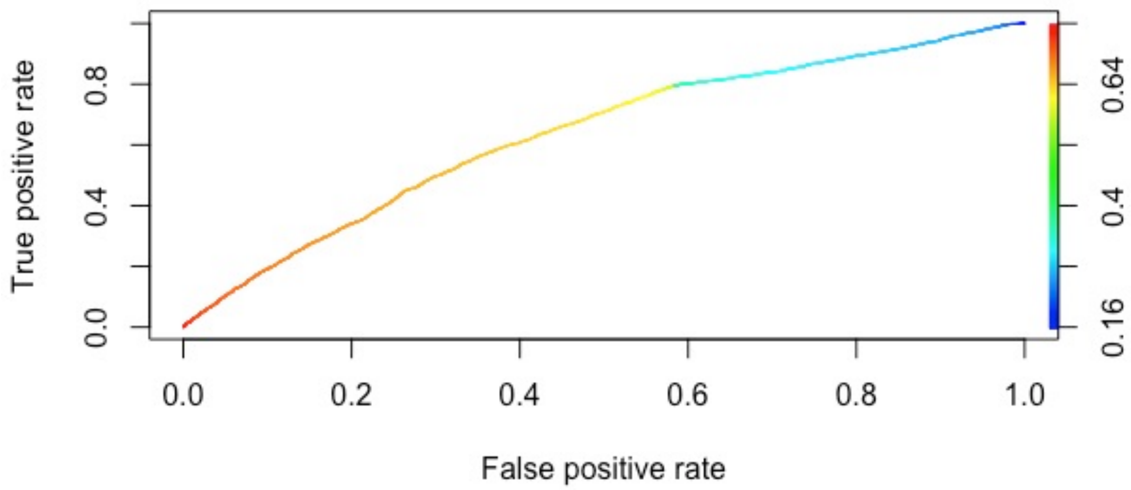
This table contrasts the predicted consistency with the actual consistency in intention-behavior of investors from the second data set. The two green highlighted boxes represent correctly predicted behaviors, while the other two boxes summarize the falsely predicted cases. The percentages in parentheses depict the share of investors with consistent or inconsistent behavior we predicted as consistent or inconsistent and add up to 100% for each column.

		Actual behavior	
		Consistent	**Inconsistent**
Predicted behavior	**Consistent**	4,348 (80%)	2,629 (58%)
	Inconsistent	1,118 (20%)	1,875 (42%)

The ROC curve gives a visual presentation of the accuracy of our prediction contrasting the TPR and FPR for every possible threshold value (*Figure 3*). A straight 45-degree line through the coordinates (0,0) and (1,1) would indicate the model classifies investors as consistent or inconsistent by pure chance (Mandrekar, 2010). On the contrary, a rectangular-shaped line would signal that the model can perfectly distinguish between consistent and inconsistent investors. Based on the ROC curve, we can derive the optimal probability threshold. Different methods exist for determining an optimal threshold depending on the goal of the analysis (Greiner et al., 2000). As in our analysis, sensitivity (Se), the probability of a true positive, and specificity (Sp), the probability of a true negative, are equally important, we maximize the Youden Index, which is defined as $J = Se + Sp - 1$ (Fluss et al., 2005; Youden, 1950). Based on this, we find that the optimal threshold is 0.4926, with Se corresponding to 0.7954, indicating we correctly predict 79.5% of the intention-behavior consistent investors as consistent. With an Sp of 0.4163, we correctly predict 41.6% of the intention-behavior inconsistent investors as inconsistent. It should be noted that this optimized threshold results in the same number of correctly and incorrectly consistency-classified investors as with our original 50% probability threshold value (*Table 11*), which can be explained by the distribution of estimated probabilities (*Appendix 9*). We observe that no cases around the 50% probability mark exist, implying that a slightly lower or higher threshold will not impact the classification. Another measure of the performance of our prediction is the underlying AUC value, corresponding to 0.6241 in our case. This indicates that the probability that a random consistent investor is ranked before a random inconsistent investor is 62.4% (Flach et al., 2011).

Figure 3: ROC curve

This figure plots the ROC curve, a visual illustration of the interplay of the TPR, the percentage of correctly classifying consistent investors as consistent, and the FPR, the percentage of falsely classifying inconsistent investors as consistent.



6. Discussion, implications, and limitations

We aimed to shed light on investors' intention-behavior consistency and inconsistency in times of stock market downturns and to identify variables influencing this relationship. This chapter will discuss our findings and highlight several consequential implications for the robo-advisor company providing the data sets and its investors. Further, we will elaborate on the limitations. It is noteworthy that our findings may not be applicable to the whole robo-advisory industry, as we analyze data of one specific robo-advisor only.

6.1. Discussion

Overall, our findings support our hypothesis that investors often do not act as they have intended during times of stock market downturns. We propose that these observations can be partially explained by declining discount rates, self-control failure, myopia, and, therefore, self-regulatory failure. More specifically, we hypothesize that many investors of our data sets lack sufficient self-control capabilities and give in to their emotions and that those investors who do have a high degree of self-control have not foreseen the far-reaching impacts the stock market downturn may have on other items of their household balance sheets or lives, leading to inconsistencies. Since we did not directly test for self-regulatory failure due to a lack of data availability, further research will be needed to investigate whether our suppositions hold true.

Further, more research is required on whether investors did experience an “illusion of commitment” and took on more risk than they could bear, resulting in discrepancies in the intention-behavior relationship. Nevertheless, we believe that in the context of the robo-advisor company providing the data, our results of intention-behavior consistency can be generalized to some extent, since they have been prominent in two different data sets and therefore in two different stock market downturns, with more than two and a half years between them. Even though stock market downturns can hardly be made comparable, as they occur with uncertainty and various influential contextual factors, we observe the same direction between the tested variables across the two data sets, and hence, in two market downturns with different causes and contextual accompanying factors. As the robo-advisor company, we retrieved the data from may not adequately represent all robo-advisors as investment platforms, more research is needed to investigate the applicability of our findings on other robo-advisory companies.

Our analyses show support for our hypothesis that investors with intentions to "hold stocks" act more consistently than investors with intentions to "sell stocks" or "buy stocks" (Hypothesis 2), statistically significant at the 0.1% level. As hypothesized, we suggest that intentions for inaction require less effort and self-control, and therefore, investors with intentions to "hold stocks" show higher intention-behavior consistency. Additional research is needed to test if our suggestions hold true and whether other influential factors exist.

Moreover, our findings support the hypothesis that investors show higher intention-behavior consistency with increasing age (Hypothesis 3), statistically significant at the 5% level. We suppose that to some extent this can be attributed to more life experience, and consequently better forecasting skills and lower hyperbolic discounting. Our observation might also be caused by attentional control increasing with age. Further research is needed to assess whether the observed effect is truly based on our suggested reasoning or whether other variables also take part in it.

Furthermore, our hypothesis regarding the relationship between intention-behavior consistency and gender (Hypothesis 4) has been accepted, in a way that the variable gender has a statistically significant influence at the 1% level. Thus, our findings support that investors who identify as female act more consistently than investors who identify as male. We propose that to some degree this observation is related to females possessing higher self-regulatory capacities and greater abilities for controlling attention and impulses. Additional research is needed to investigate whether our reasoning holds true and whether other factors are also at play that may influence the gender and intention-behavior consistency relationship.

Our results reject our hypothesis that investors with a shorter time between the onboarding and the stock market downturn, and therefore between the intention formation and the behavior observation, show higher intention-behavior consistency than investors with a longer time (Hypothesis 5). Even though the logistic regression actually suggests a slightly positive effect with an increasing time distance, significant at the 5% level, we do not detect a clear relationship between the period between the onboarding to the robo-advisor and the stock market downturn when visualizing the data. Therefore, in our data sets, the variable TIME does not seem to clearly influence investors' intention-behavior consistency in one direction or the other. Hence, it seems that it does not affect the intention-behavior consistency that investors with a longer time span between the onboarding and the stock market downturn did not have the possibility to incorporate more relevant news into their stated intentions, had less forecasting noise, and faced lower discount rates at the time they stated their intentions than investors with a shorter time. More research is needed to investigate the reasons behind these observations.

Additionally, our hypothesis that investors with sustainability preferences act more consistently than investors without (Hypothesis 6), got rejected. In fact, there does exist a statistically negative effect at the 1% level, yet in the opposite direction of what was expected. Our results show that investors without sustainability preferences, or in other words those who invest only in a broad, highly diversified portfolio, show a higher intention-behavior consistency than investors with a portfolio that has a focus on social and environmental responsibility. Hence, either investors with sustainability preferences do not seem to possess more self-control due to their future-oriented investment goals, or other factors are at play. Additional research is needed to investigate the reasons why investors with sustainability preferences show lower intention-behavior consistency than investors without.

6.2. Implications

Based on the economic theory of hyperbolic discounting and the psychological TPB, we assume that our results relate to self-regulatory failure, hence low levels of self-control and myopia. Therefore, we suggest several implications for the robo-advisor company providing the data sets and its individual investors along the time of intention formation, the period between the intention formation and behavior execution, and the time of executing intended behavior. We believe that the robo-advisor company should especially focus their efforts on investors with intentions to “sell stocks” or “buy stocks”, younger investors, investors who identify as male, and investors with sustainability preferences as they showed higher intention-behavior inconsistency in both data sets.

Since the answers to the question we adopted in our analysis to approximate investors’ intentions are used to determine, among other factors, the allocations between stocks and bonds of the recommended portfolios, they have an impact on the investors’ risk-profiling. Under the assumption that investors do not manually adjust the recommended allocation, it is important that investors consider all relevant factors and news when forming their intentions and that they are aware of the possible consequences of their intended behavior. The robo-advisor may assist investors by providing them with tools to better understand relevant information they should consider when forming their intentions of how they want to act when the stock market declines. Moreover, the robo-advisor's risk profiling should neither overestimate nor underestimate investors' willingness to take on risks, resulting in a specific allocation between stocks and bonds to mitigate that investors deviate from their intentions. Also, investors should not be nudged to take more risk than they can bear by having an "illusion of commitment". Therefore, it should be further investigated how far the "illusion of commitment" related to MiFID II regulations influence investors' perception of commitment and risk-taking. Admittedly, the introduction of binding commitments, which do not offer opportunities for deviations, may be inapplicable in the context of the robo-advisor providing the data as it bears severe business model implications. Furthermore, it is crucial that the intention is formatted strongly and consciously so that it will be remembered once the situation arises. Additionally, investors should not hold conflicting intentions that might lead them to deviate from their intended behavior.

Moreover, between the intention formation and the behavior observation, investors' intentions should ideally stay persistent. Nonetheless, investors should consciously assess new information and, in case of reasonability, change their intention and, ultimately, their behavior accordingly. If the intention, for instance, for the question of whether to "sell stocks", "hold stocks", or "buy stocks" in case of a portfolio value decline of 10% within one month must be adjusted, this should be registered in their robo-advisor profile, as it may have further implications on the recommended allocation between stocks and bonds. Hence, the robo-advisor should regularly require investors to answer the onboarding question again to encompass changes of intention in their risk profiling and impede investors from taking more risks with their portfolios than they can bear.

When the situation that is supposed to cause the intended action arises, investors should keep their attentional control to remind themselves of their intentions. Further, they should implement self-regulatory measures to mitigate the chances of acting emotionally. The robo-advisor can assist investors by reminding them to focus on their intended, long-term goals and consequences instead of short-term results. More precisely, the robo-advisor may include simulations of the development of investors' portfolios when they want to initiate a withdrawal or deposit. Hence, as described in the related literature, the robo-advisor can give investors a decision aid and nudge them into acting more rationally to adhere to their passive, long-term investment strategy.

6.3. Limitations

Due to a lack of data availability, the ideal framework had to be adjusted, which is why several limitations arose within our context. First, the context for the measurement of intention and actual behavior does not exactly match and had to be approximated. Since we approximate the question of the onboarding, it could be the case that investors do not refer the question to their robo-advisory portfolio and, therefore, passive investment strategies, but rather to active investment strategies, such as holding single stocks. Also, it is possible that investors might have related the question to the entirety of their household balance sheets, which leads to them not having answered the question in regards to our interpretation. Additionally, we cannot ensure that the actual value of the stock portion of investors' portfolios with the robo-advisor lost at least 10% in value since we approximate the decline with the S&P500. Therefore, it could be the case that some investors did not encounter the situation that would have released the behavior. Furthermore, our analysis cannot ensure the temporal stability of the observed variables since our framework did not allow for a context of controlling events and news occurring to investors. We are aware that a multitude of mostly unobservable variables may influence individuals, their beliefs, intentions, and actions during times of crises and that their assessment is problematic and incomplete, and therefore these unobservable data points, particularly other items on investors' household balance sheets, may have an impact on our results that we are not able to evaluate. Due to that, investors' intentions could have changed in a way we were not able to capture. Moreover, we did not measure self-regulatory capacities and investors' discount rates but rather drew back inconsistencies in the intention-behavior relationship to these factors. Hence, the requirements of the ideal framework are not entirely given.

Additionally, the out-of-sample prediction conducted poses further limitations. Various stock market downturns are influenced by very different events, circumstances, and factors and, therefore, are barely comparable. The first stock market downturn in our analyses took place during the emergence of covid-19, so many for us unobservable factors and their interplay could have had an impact on investors' intention-behavior consistency and their household balance sheets, such as fear regarding health issues, lower expected labor income, wealth decline or liquidity constraints. The second stock market downturn in our sample emerged during a time shaped by the Ukraine-Russian war, electricity crisis, and increasing inflation, and therefore in a completely different context and influence on investors' lives and household balance sheets than the stock market downturn of the first data set.

Moreover, our data set itself indicates some limitations. Since the data set is real customer data and needed to be highly confidential, some data points were provided in bins instead of absolute numbers. Therefore, our proxied data may be skewed to some degree, as they are concentrated in the middle of each bin.

Further, the onboarding question we take as a proxy for intention does not provide a response for a non-intention, which occurs when individuals may not have formed a real intention yet, e.g., as they did not have enough time to think about it. Nevertheless, they may feel pressured to respond to the question and therefore report an intention that does not fully represent their true, underlying intention, which in turn can result in intention-behavior inconsistency.

7. Conclusion

The overall aim of this paper was to shed light on robo-advisor investors' intention-behavior consistency. Using two data sets of a Scandinavian robo-advisor, each providing anonymized data from randomly chosen 10,000 customers during stock market downturns, we investigated the intention-behavior relationship of these investors and potential influences of the variables age, gender, intentions for inaction, the time between intention formation and behavior observation, and sustainability preferences, based on the economic theory of hyperbolic discounting, the psychological TPB and consequently, self-regulation, namely self-control and myopia.

Our stepwise logistic regression revealed that nearly every second investor in the data set acted inconsistently with their intention during the stock market downturn coinciding with the emergence of covid-19. We suggest this can be drawn to low long-term discount rates, self-control failure, and imperfect foresight. Furthermore, we confirmed that investors with intentions for inaction, investors who are older, and investors who identify as female act more consistently than their corresponding counterparts. These findings are in line with existing research about intention-behavior inconsistencies, hyperbolic discounting models and self-regulatory failure. Moreover, we found that investors with sustainability preferences behave more inconsistently to their intentions than investors without. However, we did not observe a clear influence of the time between intention formation and behavior observation, namely a shorter period between the onboarding and the stock market downturn, on investors' intention-behavior consistency. Additional research will be needed to investigate the reasonings behind our observations, especially regarding sustainability preferences and time.

Due to the lack of data availability, we conducted an out-of-sample prediction that was able to correctly predict the consistency or inconsistency of 62% of examined investors during a second market downturn. Nevertheless, the investors of our second data set, during the stock market downturn in September of 2022, showed a lower degree of intention-behavior inconsistency. Even though stock market downturns can hardly be made comparable as they occur with a variety of different contextual factors, we suggest that our model incorporates some degree of generalizability to the robo-advisor company providing both data sets since the direction of the observed variables is maintained across the two data sets. Further extensions of our findings on other robo-advisor companies as investment platforms need to be investigated in the future. Since robo-advisors can also be found in other areas of personal finance than investment advice, such as debt management, tax management, lending, and mortgage uptake, future research should also be directed into the transferability of our findings to these areas.

Given these results, several implications emerge concerning the robo-advisor company we retrieved the data sets and its investors. For instance, investors should examine all relevant factors and news when forming their intentions and be aware of all possible consequences of their intended behavior, also on other items of their household balance sheets, while the robo-advisor should aid investors in doing so. Additionally, investors should not take more risk than they can bear by having an "illusion of commitment", which may arise due to MiFID II regulations. Moreover, the robo-advisor should actively give investors the option to update their intention if new information and circumstances require an investor to change their intention, to incorporate the adjustment in the investor's risk profiling and the recommended portfolio allocation between stocks and bonds. The robo-advisor can further assist investors in not acting emotionally when the situation arises by displaying the possible consequences of their actions through simulations.

Due to the limitations of our work and the deviations from the ideal framework, future research should be directed at investigating intention-behavior inconsistencies of robo-advisor investors in a more controlled setting and try to capture missing variables in our frameworks. Research should also aim at investigating robo-advisor investors' behavior in different contexts, such as different countries, cultures, and stock market cycles. Nevertheless, our analyses contribute useful insights into the growing field of robo-advisors and their investors. Despite its limitations and the restricted extent of generalizability, this work adds to the application of economic hyperbolic discounting models, the psychological TPB, self-regulation, and investor behavior and enriches it within the context of robo-advisor investors.

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Appendix

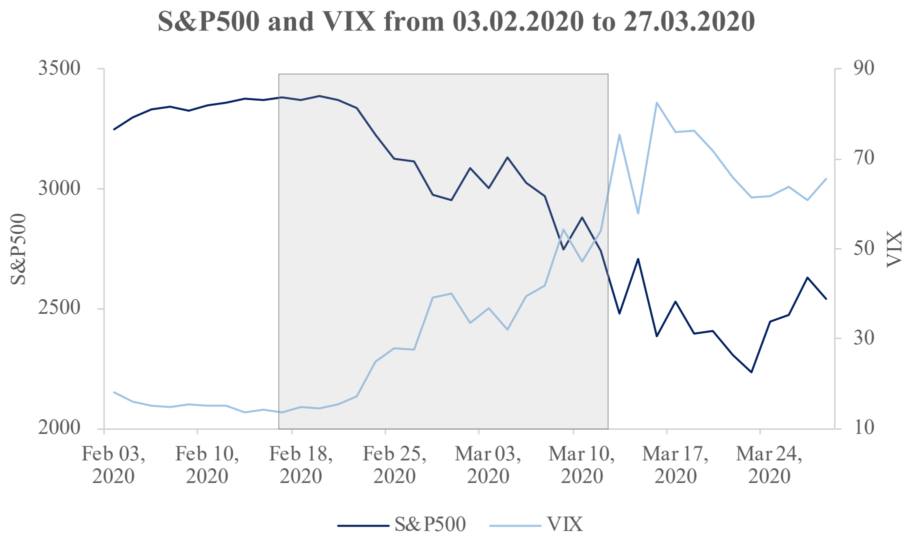
Appendix 1: Actual behavior scenarios overview

The table lists all possible activity scenarios for investors and their required conditions, sorts them into "sell stocks", "hold stocks" and "buy stocks" actual behavior categories, and gives a qualitative description of each scenario.

Actual Behavior	#	Savings Plan	Deposits	Withdrawals	Behavior (formula)	Relation of variables	Description
Sell	1	$S = 0$	$D = 0$	$W > 0$	$D - W < 0$	$D < W$	*Only withdrawn*
	2	$S = 0$	$D > 0$	$W > 0$	$D - W < 0$	$D < W$	*Deposited, but withdrawn more*
	3	$S > 0$	$D = 0$	$W = 0$	$D - W - S < 0$	$D < S$	*Original savings plan paused or canceled, no further deposits or withdrawals*
	4	$S > 0$	$D > 0$	$W > 0$	$D - W - S < 0$	$D = S$	*Deposited same amount as original savings plan, further withdrawals*
	5	$S > 0$	$D > 0$	$W = 0$	$D - W - S < 0$	$D < S$	*Deposited lower amount than original savings plan, no withdrawals*
	6	$S > 0$	$D > 0$	$W > 0$	$D - W - S < 0$	$D > S$; $D - S < W$	*Deposited higher amount than original savings plan, withdrawn higher amount than excess deposits*
	7	$S > 0$	$D = 0$	$W > 0$	$D - W - S < 0$	$D < W$	*Original savings plan paused or canceled, no further deposits but withdrawals*
	8	$S > 0$	$D > 0$	$W > 0$	$D - W - S < 0$	$D < S$	*Deposited lower amount than original savings plan, further withdrawals*
Hold	1	$S = 0$	$D = 0$	$W = 0$	$D - W = 0$	$D = W$	*No action*
	2	$S = 0$	$D > 0$	$W > 0$	$D - W = 0$	$D = W$	*Deposited and withdrawn same amount*
	3	$S > 0$	$D > 0$	$W = 0$	$D - W - S = 0$	$D = S$	*Deposited same amount as original savings plan, no withdrawals*
	4	$S > 0$	$D > 0$	$W > 0$	$D - W - S = 0$	$D > S$; $D - S = W$	*Deposited higher amount than original savings plan, withdrawn same amount as excess deposits*
Buy	1	$S = 0$	$D > 0$	$W = 0$	$D - W > 0$	$D > W$	*Only deposited*
	2	$S = 0$	$D > 0$	$W > 0$	$D - W > 0$	$D > W$	*Withdrawn, but deposited more*
	3	$S > 0$	$D > 0$	$W = 0$	$D - W - S > 0$	$D > S$	*Deposited higher amount than orginal savings plan, no withdrawals*
	4	$S > 0$	$D > 0$	$W > 0$	$D - W - S > 0$	$D > S$; $D - S > W$	*Deposited higher amount than original savings plan, withdrawn lower amount than excess deposits*

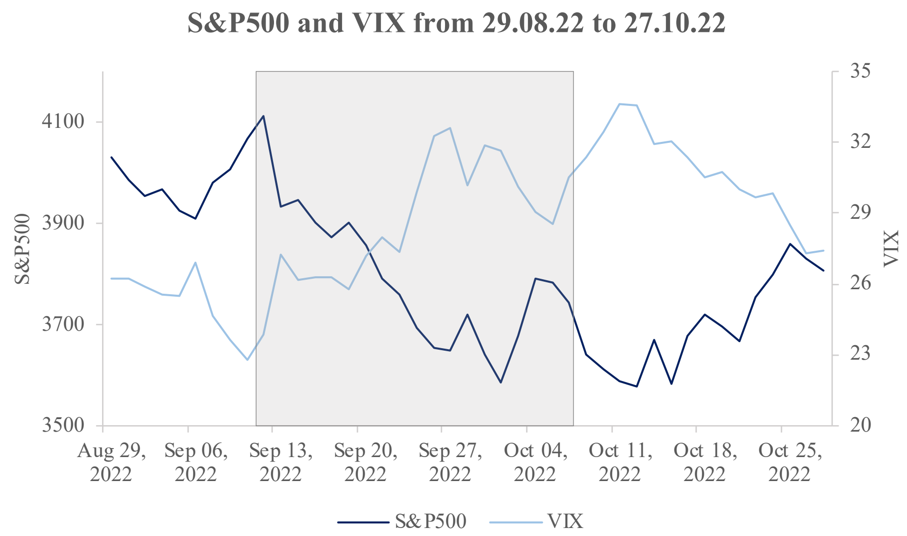
Appendix 2: S&P500 and VIX indices development from 03.02.2020 to 27.03.2020

This figure plots the development of the S&P500 index (dark blue line) on the primary y-axis and the VIX index (light blue line) on the secondary y-axis from 03.02.2020 to 27.03.2020. The highlighted grey area depicts our first considered time frame from 17.02.2020 to 13.03.2020. The underlying data was obtained through Yahoo Finance (2022).



Appendix 3: S&P500 and VIX indices development from 29.08.2022 to 27.10.2022

This figure plots the development of the S&P500 index (dark blue line) on the primary y-axis and the VIX index (light blue line) on the secondary y-axis from 29.08.2022 to 27.10.2022. The highlighted grey area depicts our second considered time frame from 12.09.2022 to 07.10.2022. The underlying data was obtained through Yahoo Finance (2022).



Appendix 4: Intention and actual behavior matrix

This contingency table lists the nine possible intention and actual behavior combinations. The three highlighted green boxes on the top-to-bottom diagonal represent intention-behavior consistency, while the other six combinations fall into the inconsistency category.

Intention		Actual behavior: Sell	Actual behavior: Hold	Actual behavior: Buy
	Sell	*Sell-Sell*	*Sell-Hold*	*Sell-Buy*
	Hold	*Hold-Sell*	*Hold-Hold*	*Hold-Buy*
	Buy	*Buy-Sell*	*Buy-Hold*	*Buy-Buy*

Appendix 5: Investors' intentions in first data set

This table summarizes the number and share of investors that have a "sell stocks", "hold stocks" and "buy stocks" intention as stated in their onboarding questionnaire when signing up to the robo-advisor and asked how they will behave in a 10% stock value decline within one month.

Intention	#	%
Sell	397	4%
Hold	6838	69%
Buy	2729	27%
Total number of investors	**9964**	**100%**

Appendix 6: Investors' actual behavior in first data set

This table summarizes the number and share of investors that showed a "sell stocks", "hold stocks" and "buy stocks" behavior during our considered time from 17.02.2020 to 13.03.2020.

Actual behavior	#	%
Sell	1148	12%
Hold	6275	63%
Buy	2541	26%
Total number of investors	**9964**	**100%**

Appendix 7: Stepwise logistic regression models

*This table presents the logistic regression output for our 5 models. Starting with the model (1) that only takes into account INT as an independent variable, we incrementally add AGE (2), GEND (3), TIME (4), and SUST to arrive at our final model (5). The p-values associated with the z value of each variable are shown in parentheses. *, **, and ***, indicate statistical significance at the 1%, 0.1% and <0.1% level, respectively. The decline in the AIC values indicates that model (5) is the best fit for our data.*

	Dependent variable:				
	CONS				
	(1)	(2)	(3)	(4)	(5)
INTSELL	-2.010***	-2.020***	-2.018***	-2.050***	-2.054***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
INTBUY	-1.514***	-1.510***	-1.495***	-1.506***	-1.509***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
AGE		0.005**	0.004**	0.004*	0.004*
		(0.005)	(0.007)	(0.017)	(0.021)
GEND			-0.096*	-0.111*	-0.126**
			(0.030)	(0.013)	(0.005)
TIME				0.0002**	0.0002*
				(0.004)	(0.021)
SUST					-0.163**
					(0.002)
Constant	0.569***	0.382***	0.443***	0.406***	0.469***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	9,964	9,964	9,964	9,964	9,964
Log Likelihood	-6,285,3	-6,281.4	-6,279.1	-6,274.9	-6,270.2
Akaike Inf. Crit.	12,576.6	12,570.9	12,568.15	12,561.8	12,554.4

Appendix 8: Odds ratios associated with the final regression model

This table summarizes the odds ratios for the independent variables of the final regression model and the corresponding 95% CIs. The odds ratios are calculated by exponentiating the regression coefficient of the examined variables.

	Independent variables:					
	INTSELL	INTBUY	AGE	GEND	TIME	SUST
Odds ratio	0.1282	0.2211	1.0038	0.8816	1.0002	0.8498
2.5%	0.0986	0.2003	1.0006	0.8074	1.00003	0.7659
97.5%	0.1647	0.2438	1.0071	0.9626	1.00037	0.9429

Appendix 9: Histogram of predicted consistency probabilities

This figure depicts the distribution of our estimated probabilities to behave consistently for each investor based on our derived logistic regression model.