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WHAT INFLUENCE DOES NUDGING HAVE ON THE HOME BIAS OF INVESTORS IN THE CONTEXT OF ROBO-ADVISORS?

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Abstract

In recent years, emerging technologies such as Robo-advisors have become increasingly relevant in the context of financial decisions-making. At the same time, behavioral biases, including home bias, persist and exert influence over investors' financial choices, leading to suboptimal portfolio performance. This study aims to provide insights on how Robo-advisors, coupled with nudging techniques, impact investors' tendencies towards home bias. To achieve this objective, a two-fold approach was adopted: firstly, a literature review was conducted to summarize existing research on the subject, followed by an empirical investigation employing a questionnaire-based online experiment. This experiment sought to evaluate the effectiveness of Robo-advisors and two nudging strategies- a warning message and default values- in reducing home bias.

The literature review underscores the potential of Robo-advisors in mitigating home bias and highlights the effectiveness of nudging techniques in addressing various behavioral biases within the context of Robo-advisors. The empirical research aimed to bridge existing gaps in understanding the effects of nudges in Robo-advisors specifically on home bias. The key findings of the empirical research reveal a significant reduction in home bias due to both nudges and the implementation of Robo-advisor technology. This indicates that there is a possibility of reducing home bias by integrating nudges into Robo-advisors and underscores the role of financial planning tools in helping users overcome decision-making biases.

Keywords: Robo-Advisor, Home Bias, Nudging, Behavioral Biases

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1 Introduction

“Why seek far afield when the good could not be any closer by?” – Johann Wolfgang von Goethe

The tendency to prefer things closer to “home” also seems to be true for capital markets. Investors tend to hold an unproportionate amount of domestic securities compared to foreign ones- a phenomenon known as home bias (Kumar & Goyal, 2015). Empirical studies have long shown that, contrary to the assumptions of traditional investment theories, investors often behave irrationally (Kahnemann & Tverky, 1979) and therefore underperform the market on average (Lisauskiene & Darskuviene, 2021). This irrational behavior is based on behavioral biases, one of them being home bias (Kumar & Goyal, 2015).

However, ongoing technological advancements are reshaping the investment industry and introducing new digital financial services, such as Robo-advisors (Lisauskiene & Darskuviene, 2021). These digital platforms guide clients through automated investment advice processes (Jung et al., 2018). Additionally, nudges, which are design decisions aimed at steering individuals towards the option they would choose if they behaved rationally, can be implemented in Robo-advisors (Jung & Weinhardt, 2018). This leads to the question if Robo-advisory services can provide a solution to help investors eliminate or at least reduce their home bias, especially when combined with nudging techniques.

This study aims to provide an answer to this question, namely determining the effect of nudges in Robo-advisors on the home bias of investors. To achieve this objective, both a literature review and empirical research were conducted, dividing the study into a theoretical (chapter 2) and an empirical part (chapter 3).

The theoretical part comprises two chapters. Chapter 2.1 clarifies key terms such as *behavioral biases*, *home bias*, *Robo-advisors* and *nudging*, laying the groundwork for understanding the paper. Chapter 2.2 then focuses on the existing research on the relationship between these three terms. It outlines the prerequisites necessary for Robo-advisors to positively influence behavioral biases, reviews previous studies on Robo-advisors' effect on home bias and other selected biases and discusses studies specifically examining nudging within Robo-advisors.

As the existing research on the effect of nudges in Robo-advisors proves to be insufficient, empirical research was conducted using a questionnaire-based online experiment, as described in the empirical part of this study. Chapter 3.1 elaborates on the research purpose and methodology, covering research questions, experimental design, methodology choice, data collection and analysis. Subsequently, chapter 3.2 presents the results of the empirical research including sample description, findings related to the Robo-advisor and the two incorporated nudges as well as their interaction.

Finally, chapter 4 discusses and interprets the results from both the literature review and empirical research, outlines study limitations and provides future research directions.

2 Theoretical framework

2.1 Fundamentals

In this chapter the necessary terms to understand the influence nudges in Robo-advisors have on home bias are introduced and explained. These include behavioral biases in general, home bias specifically, Robo-advisors and nudging.

2.1.1 Origins and effects of behavioral biases

This sub-chapter highlights the concept of behavioral biases, the reasons on why they arise, as well as the resulting behavioral gap. This lays the groundwork to understand home bias specifically and the effect Robo-advisors and nudging have on them.

In 2016, the average investor underperformed the S&P 500 stock index by 4.7% (Uhl & Rohner, 2018). This disparity between stock indices' performance and that of average investors is known as the behavioral gap, resulting from investors' irrational behavior (Uhl & Rohner, 2018).

Behavioral finance looks for possible explanations for this irrationality in investment behavior integrating behavioral and psychological elements into economic and financial decision-making (Kumar & Goyal, 2015). It challenges the traditional efficient market hypothesis and provides insights into why investors exhibit specific behaviors when investing in financial assets (Kumar & Goyal, 2015). Behavioral finance suggests that behavioral biases influence the investment decision-making process, causing investors to depart from rationality (Bhandari et al., 2008). Behavioral biases are therefore cognitive distortions that prompt investors to make irrational decisions, resulting in lower returns (Bhandari et al., 2008).

Behavioral biases occur because of uncertainty and limited time in real markets, encouraging individuals to rely on heuristics as mental shortcuts (Tversky and Kahnemann, 1974). Although these automate and simplify problem solving, they can also cause a deviation from rational behavior such as behavioral biases (Tversky and Kahnemann, 1974).

According to Kahnemann (2012), decisions are made based on two different systems: an intuitive, automatic and very fast-reacting system (System 1) and a slower, but more reflective and logically calculating system (System 2). Heuristics and, accordingly, behavioral biases arise when investors make decisions utilizing System 1, even though they may have planned to behave rationally (Kahnemann, 2012).

Now that the broader term *behavioral bias* has been explained, the more specific *home bias* will be introduced.

2.1.2 Explanation of home bias and its manifestations

Home bias describes a particular type of behavioral bias (Kumar & Goyal, 2015). In the following, the phenomenon “home bias” will be clarified and its effect on the performance of a portfolio explained.

Nineteenth century economics called them “the disinclination of capital to migrate” (reported in: Flandreau, 2006). In other words, home biases describe the tendency of investors to hold domestic securities rather than foreign securities in their portfolio (Kumar & Goyal, 2015).

According to conventional financial theory, if capital is fully mobile across borders, investors are expected to maintain a diversified portfolio of stocks globally (Coeurdacier & Rey, 2013). However, investors tend to hold a disproportionate share of local shares and hesitate to take full advantage of international diversification. This was already discovered by French and Poterba, 1991: In their sample, they found a 0.938 weight in domestic assets for US investors and a 0.9811 weight for Japanese investors. Surprisingly, even with better financial connections globally, this bias has not decreased much. In 2007, still more than 80 percent of stocks held by U.S. investors were from the U.S., which is much more than the U.S. share in the world market (Kumar & Goyal, 2015). Additionally, various other studies such as those conducted by Coval and Moskowitz (1999), Ahearne et al. (2004), Fidora et al. (2007), and Lütje and Menkhoff (2007) validate the enduring presence of home bias. Moreover, some of these studies provide evidence indicating that professional investment managers show a tendency toward this bias too.

As mentioned in chapter 2.1, numerous research studies confirm that behavioral biases in general have a negative effect on the performance of a portfolio. However, the question remains if this is also the case for home bias or if factors such as increased transaction costs for foreign assets, double taxation, currency risk, and information asymmetries could provide a rational explanation for the preference of overweighting domestic assets (Scholz et al., 2021). Nevertheless, various research studies demonstrate that inadequate international diversification tends to have a notably negative impact on the overall performance of a portfolio, as illustrated by findings from French and Poterba (1991), Tesar and Werner (1995), Lütje and Menkhoff (2007), and Seasholes and Zhu (2010).

Concluding, home biases continue to exist and negatively affect the performance of a portfolio. Other specific biases with similar effects will be explained in the next sub-chapter.

2.1.3 Other specific behavioral biases

Certain studies do not focus on behavioral biases in general or home bias but on other specific behavioral biases, such as the disposition effect, trend-chasing, the rank effect, decision inertia and ambiguity aversion. As the findings on these alternative behavioral biases contribute to gaining new insights into home bias, these studies are also relevant. For this reason, the other types of behavioral bias mentioned above will be briefly explained here.

The disposition effect describes the tendency of investors to hold on to positions whose value has decreased and to sell those whose value has increased (Kumar & Goyal, 2015).

Trend-chasing is the inclination of investors to buy a stock after a series of price increases. Investors expect that after such a series of positive returns, the price is more likely to rise than fall (D'Acunto et al., 2019).

The rank effect describes investors' tendency to sell the best and worst-performing portfolios. Portfolios that perform moderately are more likely to be ignored (D'Acunto et al., 2019).

Decision inertia describes a person's resistance to change (Jung et al., 2018). Specifically, it describes the tendency to repeat a decision regardless of its outcomes and implications (Jung et al., 2018).

Ambiguity aversion refers to individuals' tendency to feel uncertain or conflicted when faced with contradictory, incomplete, or excessive information, often leading to contradictory decisions (Ellsberg, 1961).

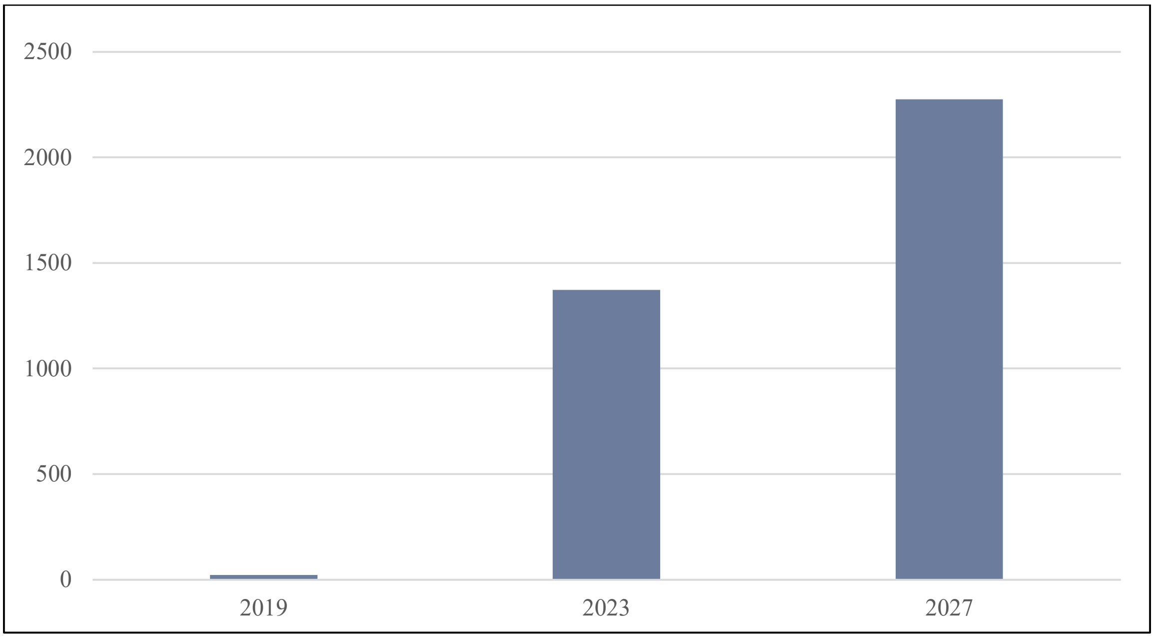
Having clarified the overarching term *behavioral bias*, along with the specific bias *home bias* and other pertinent biases, the subsequent two sub-chapters will delve into the remaining terms, *Robo-advisors* and *nudging*.

2.1.4 Functionality of Robo-advisors

As has been explained in the sub-chapters before, behavioral biases including home biases have a negative effect on investors' performances. Robo-advisors could provide a solution to this problem. This sub-chapter describes the characteristics of Robo-advisors and explains how they work.

In the course of digitization an increasing number of intelligent services based on algorithms and intelligent software have emerged, which has also led to a growing interest in digital financial advice – Robo-advisory (Jung et al., 2018). As shown in Figure 1, the number assets managed by Robo-advisors is increasing constantly and is expected to reach a total amount of US$ 2,274bn by 2027 (Statista Market Insights, 2024).

Figure 1. Assets worldwide under management of Robo-advisors
(in billion U.S. dollars)



Source: Statista Market Insights, 2024

Robo-advisors are digital platforms that provide customers with automated investment advice (Fan & Chatterjee, 2020). They differ from other existing online investment platforms, particularly in customer evaluation and portfolio management (Jung et al., 2018). They transform the entire traditional human-to-human advisory process into a human-to-computer process (Jung et al., 2018). The investor's profile is no longer created through personal interviews but rather through online questionnaires and self-reporting processes (Fan & Chatterjee, 2020). Algorithms and automated processes then quantify the respective investment goals, risk affinity, and return expectations (Fan & Chatterjee, 2020).

With this data algorithms can make recommendations for investment decisions or even make the decision themselves and initiate corresponding actions (Lisauskiene & Darskuviene, 2021). Thus, a distinction is made between a passive approach, where a portfolio is automatically assembled and an active approach, where the investor can choose between various suggestions from the Robo-advisor or modify the proposed portfolio (Lisauskiene & Darskuviene, 2021).

Robo-advisors can help improve investor performance (Uhl & Rohner, 2018). This is achieved by increasing portfolio diversification and reducing volatility (D'Acunto et al., 2019), as well as avoiding costs such as high management and product fees (Uhl & Rohner, 2018).

This paper focuses on the question if Robo-advisors- additionally to investor performance- can also reduce home bias, especially by using nudging, a concept that will be explained in the next sub-chapter.

2.1.5 Description of nudging and digital nudging

Nudges are behavioral interventions or design choices that steer consumers or investors toward the option they would have chosen if they were making decisions and acting rationally (Sunstein, 2014). Nudges are already widely used by user interface designers (Jung et al., 2018) or financial advisers (Thaler & Benartzi, 2004) to positively influence the decision-making of participants. Commonly employed nudges include setting defaults, offering incentives and delivering feedback (Thaler et al., 2010; see Table 1).

Table 1. Selection of nudge principles, descriptions, and examples

Nudge principle	**Description**	**Example**
Defaults	Preselecting options by setting default options	Changing defaults (from opt-in to opt-out) to increase the percentage of people who consent to being organ doners
Incentive	Making incentives more salient to increase their effectiveness	Telephones that are programmed to display the running cost of phone calls
Giving feedback	Providing users with feedback when they are doing well or making mistakes	Electronic road signs with smiling or sad faces depending on the vehicle's speed

Source: Weinmann et al., 2016, p. 435

In recent times, *digital nudges* have also gained increasing attention (Jung et al., 2018). In this context, elements of the user interface such as wording, notifications or specific support functions are utilized to guide users in the desired direction (Weinmann et al., 2016). Previously mentioned nudges, such as setting defaults or providing feedback, can be adapted for digital environments and transformed into digital nudges (Weinmann et al., 2016). Although this concept is still relatively new, there are already studies using digital nudges to mitigate biases in user-generated online reviews (Schneider et al., 2015) or promote environmentally conscious decision-making in online bookings (Székely et al., 2016).

The present research suggests that both nudges and digital nudges have the potential to assist decision-makers in achieving optimal outcomes in financial decisions. The existing studies that investigate whether nudges in Robo-advisors can also reduce behavioral biases will be presented in the course of the next chapter.

2.2 Literature review

With the basic concepts and fundamental terms clarified, this chapter focuses on the relationship between those terms and the existing research in this field. This includes the prerequisites that must be fulfilled for Robo-advisors to have a positive impact on home bias, the existing research on the influence of Robo-advisors on home bias as well as other behavioral biases and a review of the literature on nudges in Robo-advisors and their influence on behavioral biases.

2.2.1 Prerequisites for positive impact of Robo-Advisors on home bias

There are certain requirements that Robo-advisors and their design must meet in order for them to positively influence home bias and other behavioral biases. These are described in the following.

Robo-advisors are programmed and designed by humans (Bhatia et al., 2020). The development of Robo-advisors itself has an impact on whether they will be able to mitigate the behavioral biases of investors (Bhatia et al., 2020). Only if Robo-advisors themselves are free from biases, they can reduce or even eliminate biases in users (Bhatia et al., 2020). Therefore, it is crucial that developers of Robo-advisors are aware of biases so that they can eliminate them from questionnaires and Robo-advisors in general (Bhatia et al., 2020). If programmers use Kahneman's second, rational system, Behavioral biases of System 1 in investors could be prevented (Lisauskiene & Darskuviene, 2021).

Furthermore, it is essential for the success of Robo-advisors that they employ a strict rebalancing system instead of attempting to time the market (Uhl & Rohner, 2018). This means they aim to bring the investor's portfolio back into balance, restoring the original portfolio allocation (Uhl & Rohner, 2018). This not only ensures adherence to the risk-return profile but also avoids the behavioral gap (Uhl & Rohner, 2018).

If all these prerequisites are fulfilled, they can have a positive influence on home bias. The studies that investigate this influence are presented in the following sub-chapter.

2.2.2 Influence of Robo-Advisors on home bias

Several existing studies have explored the influence the use of Robo-advisors has on the home bias of investors. The results of these studies are highly relevant to this paper and are outlined in this sub-chapter.

Loos et al. (2020) compared the decisions of individual investors before and after having access to Robo-advise services in a field experiment, using data from a large German retail bank. They found that Robo-advisors do not eliminate, but significantly reduce home bias of individual investors. After starting to use Robo-advisors, investors increased their portfolio diversification, including geographical diversification: Home bias reduced by 28.5% of the mean value (Loos et al., 2020). The pronounced effect was typically stronger on former self-directed investors compared to investors who have previously collaborated with a human financial advisor (Loos et al., 2020). The Robo-advisor used in their study incorporated nudges, such as a default selection of products following the client's active choice of an asset class (Loos et al., 2020). However, Loos et al. (2020) did not examine the influence these nudges had on the investor’s decision but focused on the overall effect the use of the Robo-advisor had on home bias and other factors.

Scholz et al. (2021) investigated if Robo-advisors are free from home bias. They compared the domestic quotas of the largest Robo-advisors of three countries (US, UK, and Germany) to the respective share of this country in the MSCI World Index as well as the global gross domestic product. They found that most Robo-advisors allocate a higher proportion to domestic stocks than these criteria would indicate, especially in the US and in the UK. According to Scholz et al. (2021), these findings suggest that Robo-advisors are not immune to home bias. The results also indicate that Robo-advisors relying on investment committees rather than rule-based allocations tend to be more prone to home bias (Scholz et al., 2021).

Rossi and Utkus (2020) examine the impacts of a large U.S. Robo-advisor on investors who were previously self-directed. Among various other aspects, their study addresses the impact on home bias in their portfolios. The study shows a significant reduction in home bias, which can be attributed to improved diversification through higher allocations to international equities and fixed-income securities (Rossi & Utkus, 2020).

Table 2. Overview of existing studies on influence of Robo-advisors on home bias

Source	**Results**	**Research method**
Loos et al. (2020)	Robo-advisors reduce, but do not eliminate home bias	Field experiment
Scholz et al. (2021)	Robo-advisors are not immune to home bias	Comparative analysis
Rossi & Utkus (2020)	Robo-advisors reduce home bias	Data analysis

Source: Own representation

Table 2 summarizes the existing studies that investigate the influence of Robo-advisors on home bias: The findings of Loos et al. (2020) and Rossi and Utkus (2020) indicate that the home bias of investors significantly is reduced after the use of a Robo-advisor, whereas the results of Scholz et al. (2021) show that Robo-advisors are not exempt from home bias. To gain a wider range of results, the following sub-chapter focuses on studies that examine the influence of Robo-advisors on other behavioral biases.

2.2.3 Influence of Robo-Advisors on behavioral biases

Home biases fall within the category of behavioral biases. Therefore, the outcomes of studies investigating the impact of Robo-advisors on behavioral biases in general, as well as other specific behavioral biases, hold relevance. Numerous studies have examined the influence of Robo-advisors on investors' behavioral biases, with most of them focusing on distinct behavioral biases rather than a broad exploration of behavioral biases in general (Lisauskiene & Darskuviene, 2021). In the following, the findings of relevant studies that explore behavioral biases other than home bias will be presented. Various methods have been applied, ranging from interviews and field experiments to laboratory experiments or real-time studies (Lisauskiene & Darskuviene, 2021).

The disposition effect is highly present among human professional investors and significantly influences their investment behavior (Liaudinskas, 2019). In algorithms, on the other hand, this effect is almost nonexistent (Liaudinskas, 2019). This would suggest that the automation of the decision-making process could help avoid the disposition effect (Lisauskiene & Darskuviene, 2021).

According to D'Acunto et al. (2019), Robo-advisors cannot completely eliminate this effect but can only reduce it. In a field experiment the decisions of individual investors before and after using Robo-advisors were compared (D'Acunto et al., 2019). The disposition effect was, on average, reduced by approximately 30% (D'Acunto et al., 2019). For investors who exhibited a disposition effect before using the Robo-advisor the results are more conclusive (D'Acunto et al., 2019). Among investors with a low manifestation of the disposition effect before use 60% showed a reduction and among those with a high manifestation 85% showed a reduction (D'Acunto et al., 2019).

The same study (D'Acunto et al., 2019) compared the degree of trend-chasing and rank effect of investors before and after using Robo-advisors. Similar results were obtained: behavioral biases can be reduced, but not eliminated (D'Acunto et al., 2019). They also found the positive effect of the Robo-advisor on trend-chasing to be much less pronounced than the disposition effect (D'Acunto et al., 2019). Here, a reduction of just 1.2% was observed (D'Acunto et al., 2019). However, Loos et al. (2020) also found that investors' trend-chasing was lowered after using a Robo-advising service.

Regarding the rank effect it was found that the tendency to sell well-performing stocks compared to mediocre-performing ones could be reduced by the Robo-advisor (D'Acunto et al., 2019). A reduction of about 26% was observed (D'Acunto et al., 2019). However, no significant difference was observed for medium and poorly performing stocks after using the Robo-advisor (D'Acunto et al., 2019). This can be explained by the limited initial tendency to sell stocks with the worst performance in the sample (D'Acunto et al., 2019).

Jung and Weinhardt (2018) investigated in a laboratory experiment to what extent Robo-advisors can help reduce decision inertia. The results suggest that Robo-advisors can have a significant impact on the reduction of decision inertia (Jung & Weinhardt, 2018). This laboratory experiment involved various types of nudges, which will be discussed further in the next chapter.

Uhl and Rohner (2018) examined how Robo-advisors recommending portfolios composed of index funds rather than individual stocks influence behavioral biases. They also concluded that behavioral biases can be reduced by Robo-advisors (Uhl & Rohner, 2018). According to their calculations, the behavioral gap between a Robo-advisor and an average investor is 4.4% per year and even when considering management fees, etc., it remains at 2.9% (Uhl & Rohner, 2018).

Table 3. Overview of existing studies on influence of Robo-advisors on behavioral biases

Examined behavioral bias	**Results**	**Research method**	**Source**
Disposition effect	Hardly any disposition effect observed among algorithmic traders	Field experiment	Liaudinskas (2019)
	Robo-advisors reduce the disposition effect, but do not eradicate it	Field experiment	D'Acunto et al. (2019)
Trend-chasing	Robo-advisors reduce trend-chasing, but do not eradicate it	Field experiment	D'Acunto et al. (2019)
	Robo-advisors reduce trend-chasing	Field experiment	Loos et al. (2020)
Rank effect	Robo-advisors reduce the rank effect, but do not eradicate it	Field experiment	D'Acunto et al. (2019)
Decision inertia	Robo-advisors reduce decision inertia	Laboratory experiment	Jung & Weinhardt (2018)
Behavioral biases in general	Robo-advisors reduce behavioral biases	Real-time experiment	Uhl & Rohner (2018)

Source: Own representation

Table 3 summarizes the existing literature on the influence of Robo-advisors on behavioral biases. The results from all these studies suggest that Robo-advisors have an impact on the behavioral biases of investors and can help reduce them. In the next sub-chapter, the role that nudging has in this will be examined.

2.2.4 Nudges in Robo-advisors and their influence on behavioral biases

Currently, there is no extensive existing research on the impact of nudges in Robo-advisors on home bias. However, such research does exist for behavioral biases in general and specific other behavioral biases, such as overconfidence and decision inertia. As these findings are highly relevant for understanding potential interconnected effects related to home biases and determining effective techniques, they are presented in the following.

The selection of a nudge depends on the Robo-advisor's operational approach (Lisauskiene & Darskuviene, 2021). Certain Robo-advisors make investment decisions autonomously and without direct input from the investor, constituting a passive investment approach (Lisauskiene & Darskuviene, 2021). On the other hand, if the Robo-advisor guides the investor towards the optimal choice while simultaneously presenting several options, this represents an active investment approach (Lisauskiene & Darskuviene, 2021).

According to Jung and Weinhardt (2018), a similar distinction can be made between nudges that enable active decision-making and those that only allow passive decision-making. In a nudge associated with active decision-making, the deliberative system (System 2) is activated, while in a nudge associated with passive decision-making, the automatic system (System 1) is activated (Jung & Weinhardt, 2018). Additionally, active decision-making induces a learning effect, which is not the case with a passive approach (Jung & Weinhardt, 2018).

An active approach targeting the deliberative system was applied by Bhandari et al. (2008) using a decision support system. In an experiment, investors' risk tolerance and level of overconfidence were determined using questionnaires (Bhandari et al., 2008). Subsequently, feedback in the form of text and graphical representations was provided to the participants based on their responses (Bhandari et al., 2008). The results of the experiment show that nudging was successful in reducing behavioral biases (Bhandari et al., 2008).

Another nudge that allows for active decision-making is warning messages (Sunstein, 2014). These messages are intended to encourage investors susceptible to behavioral biases to reconsider their decisions and, if necessary, consider other options (Sunstein, 2014). Jung and Weinhardt (2018) used this nudge with a Robo-advisor and found that warning messages have a significant impact on reducing decision inertia in an investor.

In the same laboratory experiment default nudges were also examined, allowing only passive decision-making (Jung & Weinhardt, 2018). Default nudges mean that the rationally best option is pre-selected for the investor (Jung et al., 2018). The experiment showed that this form of nudge can also reduce decision inertia (Lisauskiene & Darskuviene, 2021).

As both approaches have proven successful in experiments, the question arises whether nudges in Robo-advisors that allow for active investment decisions or those that do not are better suited to reduce behavioral biases. Jung and Weinhardt (2018) concluded by comparing warning messages and default nudges that default nudges are better suited to address decision inertia.

However, Braeuer et al. (2017) found in their experiment that even though the Robo-advisor provided a default value, investors who were financially capable chose to invest more. Their results indicate that investors select their contribution rates to saving plans based on their wealth rather than adhering to the default values (Braeuer et al., 2017). They investigated behavioral biases in general by using data from a large German bank (Braeuer et al., 2017).

Table 4. Types of nudges used in existing studies to influence behavioral biases

Nudges used	Examined behavioral bias	Results	Research method	Source
Feedback in the form of text and graphical representations	Ambiguity aversion	Nudging reduced ambiguity aversion.	Experiment; using questionnaires	Bhandari et al. (2008)
Warning message	Decision inertia	Warning messages reduced decision inertia.	Laboratory experiment	Jung & Weinhardt (2018)
Default nudges	Decision inertia	Default nudges reduced decision inertia even more than warning messages	Laboratory experiment	Jung & Weinhardt (2018)
Default nudges	Behavioral biases in general	The default value did not influence investors' contribution rate.	Field experiment	Braeuer et al. (2017)

Source: Own representation

Table 4 summarizes the existing literature on the influence of nudges in Robo-advisors on behavioral biases. It shows that the effectiveness of nudges in Robo-advisors has been demonstrated in various studies but has also yielded negative results in the case of Braeuer et al. (2017). The studies also indicate that when comparing an active and passive approach, the passive approach has presented more successful results.

This chapter marks the conclusion of the theoretical part, with subsequent chapters covering the empirical part of this study.

3 Empirical research

3.1 Research purpose and methodology

This chapter outlines the methodological approach of the empirical investigation. Firstly, it delves into the objectives and research questions. Subsequently, the experimental design is outlined. Following this, the reasoning behind the choice of methodology is provided. Finally, the data collection, data analysis and statistical tests are detailed.

3.1.1 Objectives and research questions

Despite the growing importance of Robo-advisors and nudging as well as the recognized negative effect of home bias on a portfolio’s performance, there is, as mentioned in the chapter before, currently no extensive research on all three variables. The main objective of the following empirical research is to fill this gap by evaluating how nudging, within the context of Robo-advisors, influences investors' tendency towards home bias.

To achieve this, the empirical research focuses on the following research questions (RQ):

RQ1: Does a recommendation from a Robo-advisor positively influence the reduction of investors' home biases?

RQ2: Does nudging positively influence the reduction of investors' home bias?

RQ3: Does the nudge *warning message* or the nudge *default values* prove to be more effective in decreasing investors’ home bias in the context of Robo-advisors?

To answer these questions, a questionnaire-based online experiment was conducted. The exact methodology will be explained in the following chapters.

3.1.2 Experimental design

As mentioned, the research questions from the previous chapter were explored through a questionnaire-based online experiment. Google Forms served as the chosen survey software for data collection.

The structure of the online experiment is outlined below; the exact questionnaire can be found in the appendix of this paper.

A random variable (which part of the month the participant was born in) was employed to randomly assign participants to eight groups. Each group was tasked with an investment decision: Allocating a *significant amount of money* among a) Stocks from their home country b) Stocks from other countries c) Additional financial products from their home country and d) Additional financial products from other countries. Following this allocation task, the groups underwent three distinct treatments:

- A suggestion from a Robo-advisor on how to allocate the money
- Nudge 1: A warning message explaining home bias and its effect on a portfolio's performance
- Nudge 2: Pre-selected default values that match the Robo-advisor's suggestion

The suggestion from the Robo-advisor, as well as the default values, consist of the following percentages: a) 5% stocks from the participant's home country b) 45% stocks from other countries c) 5% additional financial products from the participant's home country and d) 45% additional financial products from other countries.

Each one of the eight groups was subject to a different combination of the three treatments, covering all possible combinations:

- Group 1 (= control group): No suggestion from Robo-advisor, no warning message, no default values
- Group 2: No suggestion from Robo-advisor, warning message, no default values
- Group 3: No suggestion from Robo-advisor, no warning message, default values
- Group 4: No suggestion from Robo-advisor, warning message, default values
- Group 5: Suggestion from Robo-advisor, no warning message, no default values

- Group 6: Suggestion from Robo-advisor, warning message, no default values
- Group 7: Suggestion from Robo-advisor, no warning message, default values
- Group 8: Suggestion from Robo-advisor, warning message, default values

Subsequently, participants answered demographic questions about their age, home country, gender, education level and investment experience. Additionally, two *manipulation checks* were incorporated to assess if the implemented nudges were perceived by the participants. Moreover, the questionnaire included an *attention check* to identify participants who may not have paid sufficient attention to the survey.

The reasoning behind the methodology outlined in this sub-chapter will be presented in the following.

3.1.3 Choice of methodology

As discussed in previous chapters, the existing literature does not definitively answer the question of the influence of nudging on investors' home bias in the context of Robo-advisors. Therefore, the literature review, which is extensively detailed in the theoretical section, is supplemented by empirical research. Based on the gap in existing knowledge specific research questions were formulated and a specific experiment was conducted to address these questions. The chosen method was a survey-based online experiment, representing quantitative research with a deductive approach (Khalid et al., 2012).

The survey method was selected for data collection because it allows for the collection of information that cannot be easily observed (Hug & Poscheschnik, 2020). This is the case in this study, especially since a laboratory experiment with the use of a Robo-advisor was not feasible due to limited resources.

In particular, an online survey was chosen primarily due to the need for a sufficiently large sample size. This approach enables reaching a significant number of participants across various countries and is widely accepted among participants, partly due to its flexibility, voluntary participation and anonymity (Nayak & Narayan, 2019). Additionally, it facilitated the implementation of default values, a warning message and a hypothetical recommendation from a Robo-advisor. Nevertheless, like any methodological approach, this method has its limitations; notably, potential issues include the risk of non-representativeness in the sample and the lack of control over data collection variables such as location, time and potential multiple participations (Nayak & Narayan, 2019).

The specific nudges *warning message* and *default values* were chosen because of their successful implementation in studies concerning other behavioral biases (e.g. Jung & Weinhardt, 2018). Moreover, warning messages allow active decision-making, whereas default nudges allow passive decision-making (Jung & Weinhardt, 2018). Therefore, the experiment also enables a comparison of an active and passive approach.

An optimal investment decision and one free of home bias depends on the investor's profile (risk affinity, investment objectives, return expectations, etc.) and their country of origin. To prevent undue complexity in the experiment resulting from variations in the recommendation from the Robo-advisor and default values based on the home country or investor profile, these values were held constant. Specifically, allocations of 5% in stocks from the participant's home country, 45% in stocks from other countries, 5% in additional investment opportunities from the participant's home country and 45% in additional investment opportunities from other countries were selected.

In previous studies (e.g. Scholz et al., 2021), researchers utilized the proportion of investors' home country's contribution to the global GDP as a metric to determine whether investors had allocated a greater portion of their portfolio to financial products from their country of origin. For this study, the value of 10% for the home country allocation (comprising 5% in stocks and 5% in other financial products) was selected. This decision was based on the observation that most countries (including Germany and Spain, likely the countries of origin for the majority of participants) contribute less than 10% to the global GDP, yet many investors tend to allocate more than this percentage to financial products from their own country. For instance, in the study conducted by Lütje and Merkhoff (2007), over 70% of German investors expressed a preference for a weighting of approximately 10% or higher for the German market.

With the structure of the questionnaire and its rationale now explained, the subsequent sub-chapters will delve into the methods employed for data collection and analysis.

3.1.4 Sample selection and data collection

The experimental design presented in previous chapters and the resulting eight groups made a sufficiently large sample necessary. To achieve this, the questionnaire was sent to contacts of the author and director, including private as well as university contacts. Moreover, the link to the survey was posted on LinkedIn. This technique was supplemented by the so-called *snowball sampling*, where study participants pass on the questionnaires to other individuals within their network. Data collection occurred between February 3, 2024, and February 13, 2024.

To ensure that the questionnaire reaches a larger audience and secures a larger sample size, it was created in three languages: English, Spanish and German. Another reason was to ensure the inclusion of participants from different home countries. Each of the three questionnaires maintains an identical structure and includes accurate translations in their respective languages.

The next subchapter will explain how the data collected in this manner was analyzed.

3.1.5 Data analysis and statistical tests

The collected data underwent quantitative analysis using the statistical software Jamovi for Windows. Prior to analysis, the data from the three questionnaires were exported from the survey software Google Forms, merged and coded in Excel. Invalid responses were identified and addressed.

To assess the presence of home bias, the total percentage allocated by participants to both stocks and other financial products from their home country was calculated. Home bias is considered to be present only when this percentage is unreasonably high. Whether this is the case will be further evaluated in a subsequent section of the study.

The data analysis encompassed both descriptive and inductive statistical methods. Descriptive analysis was employed to examine various demographic characteristics of the participants, including their distribution across their home countries, gender, age groups, level of education, and investment experience. Additionally, the proportions of participants' investments in their own home country were descriptively analyzed across all groups, as well as for each of the three treatments and the resulting eight groups.

For the inductive statistical analysis, the significance level at which the null hypothesis is rejected was set to a threshold of 0.5% ($p = 0.05$). Variable statistical tests were conducted, including a factorial ANOVA, Chi-square tests, independent samples t-tests (Mann-Whitney U) and one-way ANOVAs (Kruskal-Wallis).

Table 5 summarizes these tests and provides an explanation of the purposes for which these tests were conducted, along with their assumptions and whether these were met. The Jamovi tables for these tests can be found in the appendix.

As indicated in table 5, one of the assumptions for the factorial ANOVA—that the dependent variable's data are normally distributed—was not met. Nevertheless, given the sufficiently large sample sizes ($N > 30$), homogeneous variances, balanced group sizes and the distribution of the dependent variable, while not normal, not being excessively skewed and lacking extreme values, it was determined to proceed with conducting this statistical test.

Table 5. Summary of all conducted statistical tests

Type of test	**Investigated connection/ difference**	**Assumptions of test**	**Assumptions fulfilled?**
Chi-square test	To check the equivalence of the eight groups or their randomness in the creation (executed six times; for each one of the demographic characteristics)	- Nominal or ordinal variables - Independence of observations - Mutually exclusive groups - Expected value of cells 5 or greater	Yes
Factorial ANOVA	To evaluate the influence of the three treatments as well as their interaction on the percentage that was decided to invest in home country	- Continuous (dependent) variable - Normally distributed - Independent samples - Random sample - Sufficiently large sample size - Homogeneity of variance	Yes, except for normal distribution
Independent Samples T-Test (Mann-Whitney U)	To evaluate the influence of the implemented "randomness checks" (executed two times; for both implemented nudges) To evaluate if the demographic characteristics influence the percentage that was decided to invest in home country (executed two times; for gender and investment experience yes/no)	- Continuous (dependent) variable - Only two groups - Independent samples - Random sample - Sufficiently large sample size - Similar shape across groups	Yes
One-way ANOVA (Kruskal-Wallis)	To evaluate if the demographic characteristics influence the percentage that was decided to invest in home country (executed four times; for home country, age groups, level of education and years of investment experience)	- Continuous (dependent) variable - Random sample - Independent samples - Sufficiently large sample size - Similar spread and shape across groups	Yes

Source: Own representation

The outcomes and findings of the data analysis will be presented in the next chapter.

3.2 Presentation of results

This chapter presents the findings of the online experiment. It begins with a description of the sample, followed by the presentation of the results, which are organized into four sections: Firstly, the descriptive results across and between all groups are presented. Subsequently, the outcomes for the implemented recommendation of the Robo-advisor, the first nudge (warning message), and the second nudge (default values) are discussed in three separate subsections. Following that, one subsection delves into the results of the interaction between these three factors and offers a comparison. Finally, the potential influence of other factors such as demographic characteristics is assessed.

3.2.1 Description of the sample

This section is dedicated to describing the experiment's sample, focusing on the demographic characteristics of the participants. The Jamovi tables for these results can be found in appendix 2.1.

A total of 410 individuals participated in the experiment. An attention check question was included towards the end of the questionnaire, which two participants failed. These two participants as well as twelve other participants failed to achieve a total of 100% in the allocation question. Consequently, a total of 396 valid responses were obtained.

The majority of the participants were from Germany (73.9%), while other home countries included Spain (13.9%), France (6.8%), Ireland (3.5%) and other countries (2.5%) including USA, Brazil, Romania, Bulgaria, Latvia and Italy. 57,1% of the participants were female (42,9% male). In terms of age groups, all participants were more than 18 years old, 53.0% of participants were between 18 and 25 years old, 17.2% were between 26 and 40 years old, 25.8% were between 40 and 60 years old and 4.0% above the age of 65. Regarding education, every participant held at least a high school degree, with 58.8% listing this as the highest educational degree they had completed. Additionally, 23.2% held a bachelor's degree, 14.6% a master’s degree, 1.8% more than a master’s degree (PhD etc.) and 1.5% completed a vocational training or similar. Furthermore, 57.5% of the participants had already invested or were currently investing in stocks or other financial products (42.4% had never invested before). Among those with investment experience 29.5% had invested for less than two years, 31.3 % between two and five years, 10.1% between six and ten years, 15.9% between eleven and twenty years and 13.2% for more than twenty years.

The eight scenarios had balanced samples of 44 - 53 participants each. There were no significant differences observed in terms of gender ($p = 0.815$), age groups ($p = 0.513$), home country ($p = 0.538$), education ($p = 0.617$), investment experience ($p = 0.126$) or years of investment experience ($p = 0.536$) across the eight scenarios. The corresponding Jamovi tables can be found in the appendix 2.2.

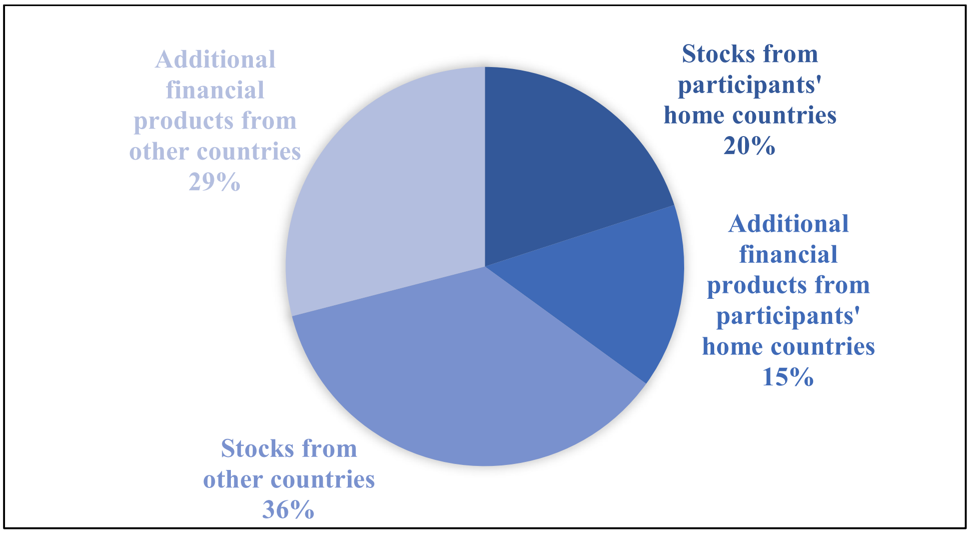
Now that the sample has been described, the next sub-chapters present the results of the experiment.

3.2.2 Descriptive results across and between all groups

This sub-chapter first describes the results across all groups, focusing on how much the participants decided to allocate to the different investment options. It then also offers an overview of the descriptive findings from all groups concerning the percentage of participants' allocation to investments in their home country.

As previously discussed, determining the presence of home bias relies on the total allocation participants made towards both stocks and other financial products from their home country. Across all groups, the mean percentage allocated to home country investments is 34.8% (median: 30.0%). Specifically, this comprises a mean allocation of 19.5% to stocks from their home country (median: 15.0%) and 15.3% to additional financial products from their home country (median: 10.0%). In contrast, the mean percentage allocated to stocks from other countries is 36.2% (median: 40.0%), while the mean allocation to additional financial products from other countries is 29.1% (median: 30.0%). Figure 2 presents these results graphically; the Jamovi tables can be found in appendix 2.3.

Figure 2. Mean percentage invested in the different investment options

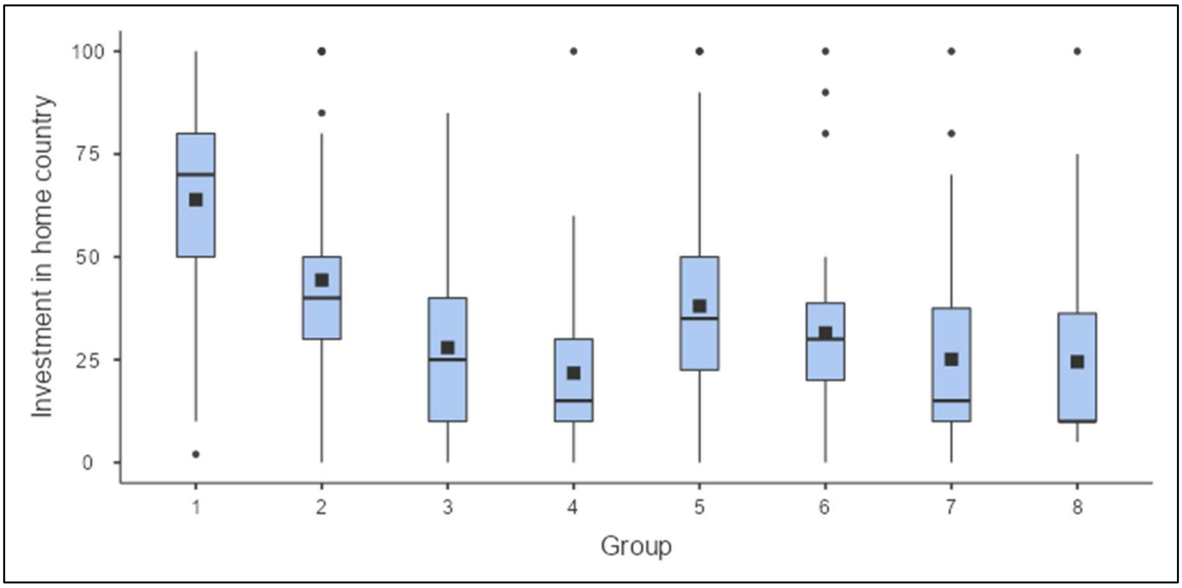


Source: Own representation

The following section fully focuses on the percentage that each of the eight groups allocated to home country investments. The mean of group 1 was 63.9% (median: 70%), of group 2 44.4% (median: 40%), of group 3 38.0% (median: 35%), of group 4 31.5% (median: 25%), of group 5 27.9% (median: 25%), of group 6 21.7% (median: 15%), of group 7 25.1% (median: 15%) and of group 8 24.5% (median: 10%).

Figure 3 offers a graphic presentation of these results.

Figure 3. *Investment in home country* by group



Source: Own representation

Table 6 summarizes the descriptive results concerning *investment in home country* and displays the treatments each group underwent (0= did not undergo this treatment, 1= underwent this treatment).

Table 6. Sum of *investment in home country* for each group

	Group	**Default values**	**Robo-advisor**	**Warning message**	**Sum of investment in home country (in %)**
Mean	1	0	0	0	63.9
	2			1	44.4
	5		1	0	38.0
	6			1	31.5
	3	1	0	0	27.9
	4			1	21.7
	7		1	0	25.1
	8			1	24.5
Median	1	0	0	0	70
	2			1	40
	5		1	0	35
	6			1	30
	3	1	0	0	25
	4			1	15
	7		1	0	15
	8			1	10
Standard deviation	1	0	0	0	24.9
	2			1	24.3
	5		1	0	22.3
	6			1	18.6
	3	1	0	0	19.3
	4			1	19.9
	7		1	0	22.3
	8			1	21.9

Source: Own representation

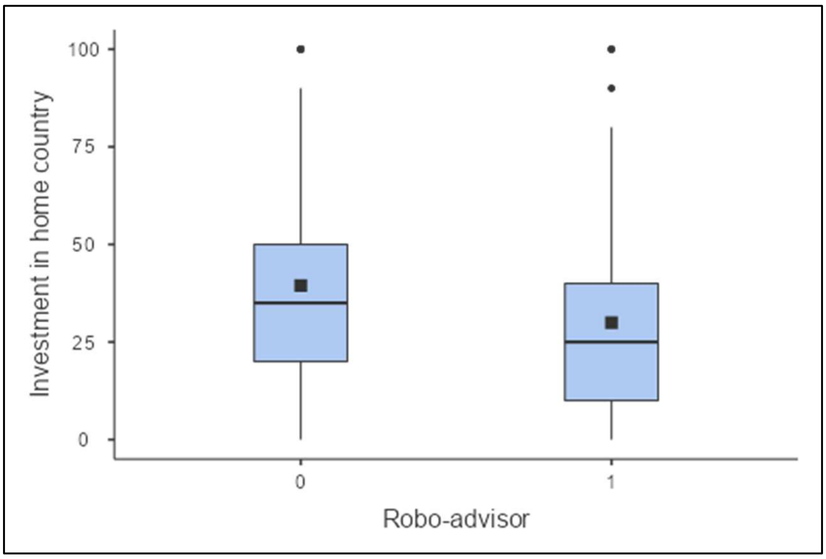
Now that the descriptive results have been outlined, the following chapters will focus on analyzing the outcomes of the implemented treatments (recommendation from the Robo-advisor, warning message and default values).

3.2.3 Results concerning the recommendation from the Robo-advisor

This sub-chapter is dedicated to presenting the outcomes related to the recommendation provided by the Robo-advisor.

In the experiment, 196 people were exposed to a recommendation from a Robo-advisor on how to allocate, while 200 people were not exposed to this recommendation. The mean of the percentage that participants without a recommendation from the Robo-advisor invested in stocks and other financial products from their home country is 39.5% (median: 30%), the one of those with a recommendation is 30.0% (median: 25%). The corresponding Jamovi can be found in the appendix 2.4; figure 4 visually presents these results (0= not exposed to recommendation of Robo-advisor; 1= exposed to recommendation of Robo-advisor).

Figure 4. Comparison of group exposed to recommendation Robo-advisor and group not exposed



Source: Own representation

To examine whether there are significant differences between the two groups, a *factorial ANOVA* was conducted. The corresponding Jamovi table can be found in the appendix 2.5. The following null hypothesis was tested:

H_0: There are no significant differences between the means of group 1 (not exposed to recommendation from Robo-advisor) and group 2 (exposed to the recommendation from Robo-advisor).

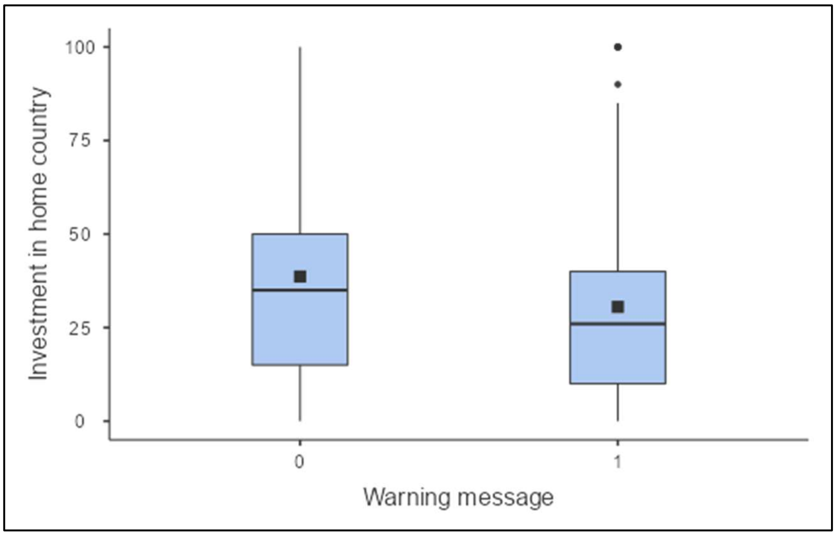
The null hypothesis was rejected ($p < 0.001$), meaning that there is a significant difference in the mean of the percentage invested in the participants' home country between those who were exposed to the recommendations of the Robo-advisor and those who were not.

3.2.4 Results concerning nudge 1: warning message

Consistent with the previous sub-chapter, this section examines the outcomes related to one of the treatments, specifically the first nudge implemented in the online experiment: the warning message.

In the experiment, 190 people were exposed to a warning message after they had made their allocation decision informing them about home bias and its negative impact on the performance of a portfolio. 206 participants were not exposed to this warning message. The mean of the percentage that participants without a warning message invested in stocks and other financial products from their home country is 38.6% (median: 35%), the one of those with the warning message is 30.5% (median: 26%). The corresponding Jamovi table can be found in the appendix 2.4; figure 5 graphically presents these results (0= not exposed to warning message; 1= exposed to warning message).

Figure 5. Comparison of group exposed to warning message and group not exposed



Source: Own representation

To examine whether there are significant differences between the two groups, a *factorial ANOVA* was conducted. The corresponding Jamovi table can be found in the appendix 2.5. The following null hypothesis was tested:

H_0: There are no significant differences between the means of group 1 (not exposed to warning message) and group 2 (exposed to warning message).

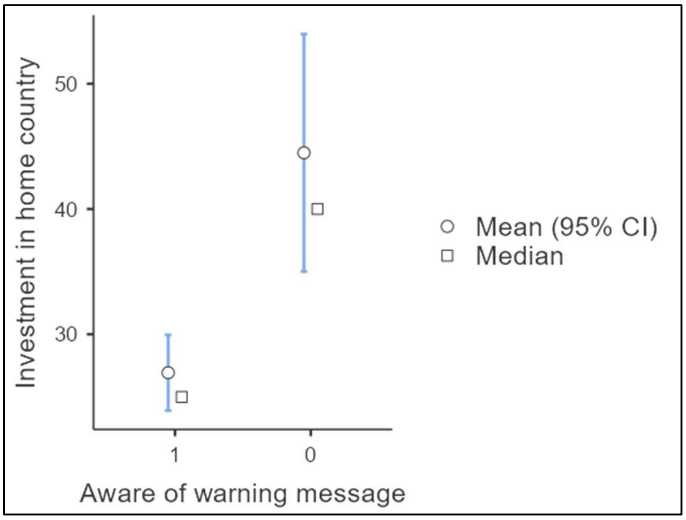
The null hypothesis was rejected ($p < 0.001$), meaning that there is a significant difference in the mean of the percentage invested in the participants' home country between those who were exposed to the warning message and those who were not.

Furthermore, the questionnaire incorporated a manipulation check to assess whether participants were aware of the warning message. To check for significant differences in the group of those who were exposed the warning message between those aware of it and those not aware, an *Independent Samples T-Test (Mann-Whitney U)* was conducted. The Jamovi table for this test can be found in the appendix 2.7. The following null hypothesis was tested:

H_0: There are no significant differences between the means of group 1 (aware of warning message) and group 2 (not aware of warning message).

The null hypothesis was rejected ($p = 0.001$), meaning that there is a significant difference in the mean of the percentage invested in the participants' home country between those who were aware of the warning message and those who were not. When looking at descriptives, the mean of the group aware of the warning message ($N = 151$) is 26.9% in stocks and other financial products from their home country, whereas the group not aware of the warning message ($N = 39$) invested 44.5% (mean) in their home country. Figure 6 represents this result graphically (0= not aware of warning message; 1= aware of warning message).

Figure 6. Differences in *investment in home country* between those aware of the warning message and those not aware



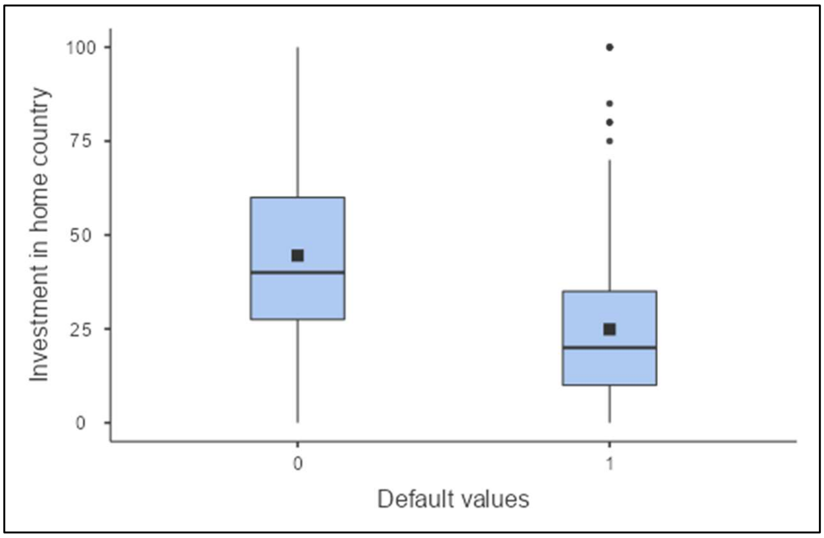
Source: Own representation

3.2.5 Results concerning nudge 2: default values

This sub-chapter outlines the results for the remaining of the three treatments, namely the default values.

In the experiment, 197 people were exposed to default values, meaning that the responses to the allocation question were already completed. 199 participants were not exposed to these default values. The mean of the percentage that participants without default values invested in stocks and other financial products from their home country is 44.5% (median: 40%), the one of those with default values is 24.9% (median: 20%). The corresponding Jamovi table can be found in the appendix 2.4; figure 7 presents these results (0= not exposed to default values; 1= exposed to default values).

Figure 7. Comparison of group exposed to default values and not exposed



Source: Own representation

To examine whether there are significant differences between the two groups, a *factorial ANOVA* was conducted. The corresponding Jamovi table can be found in the appendix 2.5. The following null hypothesis was tested:

H_0: There are no significant differences between the means of group 1 (not exposed to default values) and group 2 (exposed to default values).

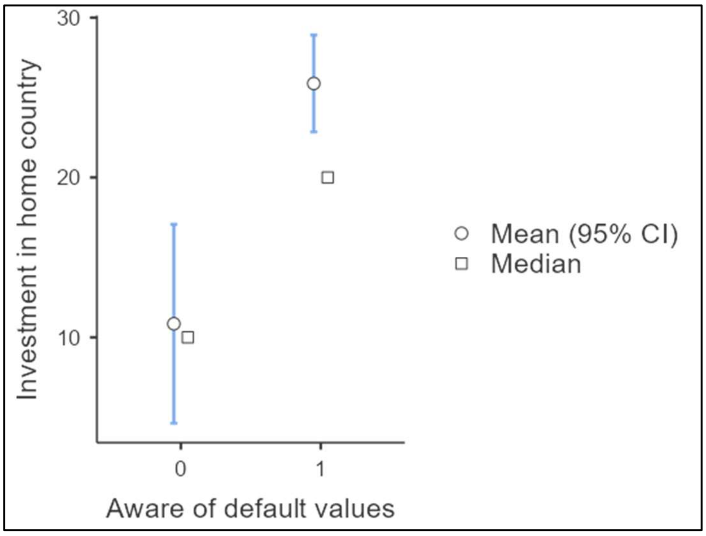
The null hypothesis was rejected ($p < 0.001$), meaning that there is a significant difference in the mean of the percentage invested in the participants' home country between those who were exposed to the default values and those who were not.

Similar to the manipulation check for the warning message, the questionnaire also included a question to verify whether participants were aware of the default values or not. To examine significant differences in the group of those who were exposed the default values between those aware of them and those not aware, an *Independent Samples T-Test (Mann-Whitney U)* was conducted. The Jamovi table for this test can be found in the appendix 2.7. The following null hypothesis was tested:

H_0: There are no significant differences between the means of group 1 (aware of default values) and group 2 (not aware of default values).

The null hypothesis was rejected ($p = 0.002$), meaning that there is a significant difference in the mean of the percentage invested in the participants' home country between those who were aware that the answers were already completed and those who were not. When looking at descriptives, the mean of the group aware of the default values (N = 184) is 25.9% in stocks and other financial products from their home country, whereas the group not aware of the default values (N = 13) invested 10.8% (mean) in their home country. Figure 8 represents this result graphically (0= not aware of default values; 1= aware of default values).

Figure 8. Differences in *investment in home country* between those aware of the default values and those not aware



Source: Own representation

Now that the individual results of the three different treatments have been presented, the next sub-chapter focuses on the interaction between these factors.

3.2.6 Treatment interactions and comparisons

This section examines the results of the *factorial ANOVA* regarding interaction effects and compares these interactions, as well as the effects of the three treatments individually. The Jamovi tables for this *factorial ANOVA* along with the corresponding *Post Hoc Tests* can be found in the appendix 2.5.

To evaluate potential significant differences between groups, a *2x2x2 factorial ANOVA* was conducted. As mentioned in the three sub-chapters before, the test found a significant effect of each one of the treatments (recommendation from Robo-advisor, warning message and default values) on the dependent variable *investment in home country*.

Apart from the effect of the individual factors/ treatments, the *factorial ANOVA* also shows the effect of the interaction of the individual factors. The following null hypotheses concerning the interactions were therefore tested:

$H_{0(1)}$: There is no significant interaction between the factor "default values" and the factor "recommendation from the Robo-advisor".

$H_{0(2)}$: There is no significant interaction between the factor "default values" and the factor "warning message".

$H_{0(3)}$: There is no significant interaction between the factor "recommendation from the Robo-advisor" and "warning message".

$H_{0(4)}$: There is no significant interaction between all three factors.

The first three null hypotheses were rejected. As the results presented in Table 7 reveal, there is a highly significant interaction between the treatments *default values* and *Robo-advisor* (p = <0.001). The interaction between the factors *default values* and *warning message* (p = 0.028) as well as the interaction *Robo-advisor* and *warning message* (p = 0.034) are also significant. However, the interaction between all three treatments is not significant (p = 0.397), the last null hypothesis was retained.

Table 7. Factorial ANOVA of *investment in home country*

	Sum of Squares	df	Mean Square	F	p	η^2p
Default values	38081	1	38081	80.369	< .001	0.172
Robo-advisor	9309	1	9309	19.647	< .001	0.048
Warning message	6689	1	6689	14.117	< .001	0.035
Default values ✻ Robo-advisor	9211	1	9211	19.440	< .001	0.048
Default values ✻ Warning message	2291	1	2291	4.834	0.028	0.012
Robo-advisor ✻ Warning message	2136	1	2136	4.508	0.034	0.011
Default values ✻ Robo-advisor ✻ Warning message	341	1	341	0.719	0.397	0.002
Residuals	183847	388	474			

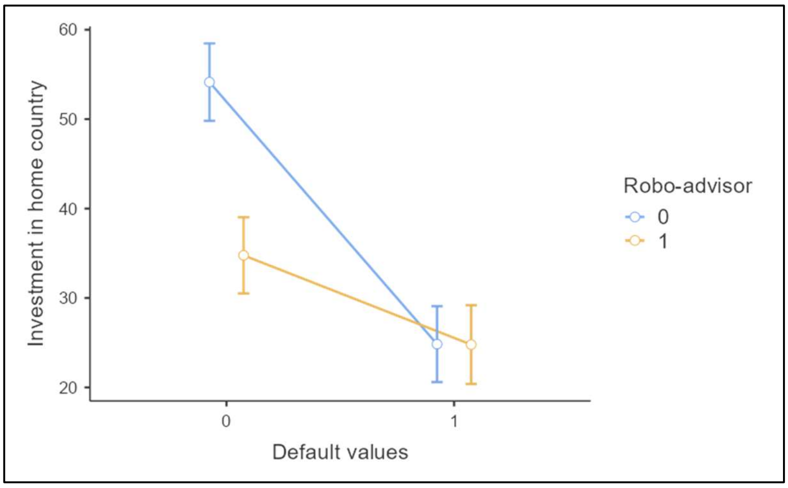
Source: Own representation

When comparing the treatments individually, the treatment *default values* has the biggest effect ($n^2p = 0.172$; mean difference = 19.6). The treatments *Robo-advisor* ($n^2p = 0.048$; mean difference = 9.71) and *warning message* ($n^2p = 0.035$; mean difference = 8.23) had a relatively similar effect, with the treatment" Robo-advisor" having a slightly stronger effect.

Regarding the interactions between the different treatments, the interaction between the treatments *default values* and *Robo-advisor* seems to be the one that influences the percentage invested in the home country the most ($n^2p = 0.048$). The interaction between the treatments *default values* and *warning message* ($n^2p = 0.012$) as well as the interaction between the treatments *Robo-advisor* and *warning message* ($n^2p = 0.011$) account for less variance in the dependent variable.

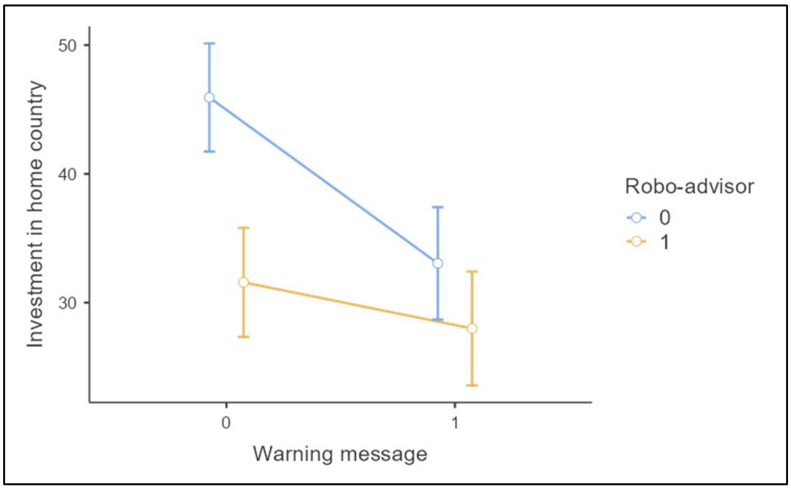
These results are also depicted in Figures 9 – 11, which visualize estimated marginal means. For instance, when analyzing the plot for *Default values * Robo-advisor*, there is a notable difference on the *investment in home country* between scenarios where there is a Robo-advisor without default values (mean = 38%) compared to when default values are active (mean = 24.8%). In contrast, when comparing this to the plot for *Warning message * Robo-advisor*, the difference in estimated marginal means between scenarios where there is a Robo-advisor but no warning message (mean = 31.6%) and when the warning message is active (mean = 28.0%) is not as prominent. The corresponding tables can be found in the appendix 2.5.

Figure 9. The effect of *default values* and *Robo-advisor* on participants' *investment in home country*



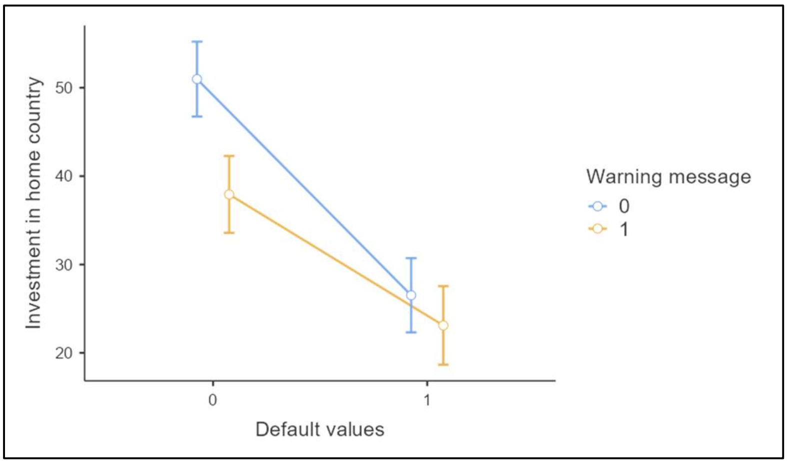
Source: Own representation

Figure 10. The effect of *warning message* and *Robo-advisor* on participants' *investment in home country*



Source: Own representation

Figure 11. The effect of *default values* and *warning message* on participants' *investment in home country*



Source: Own representation

This chapter concluded the results regarding the influence of the three treatments and their interactions on the share participants decided to invest in their own country. However, the potential influence of other variables such as investment experience, age, education, home country or gender has not yet been considered. The next chapter will examine these effects.

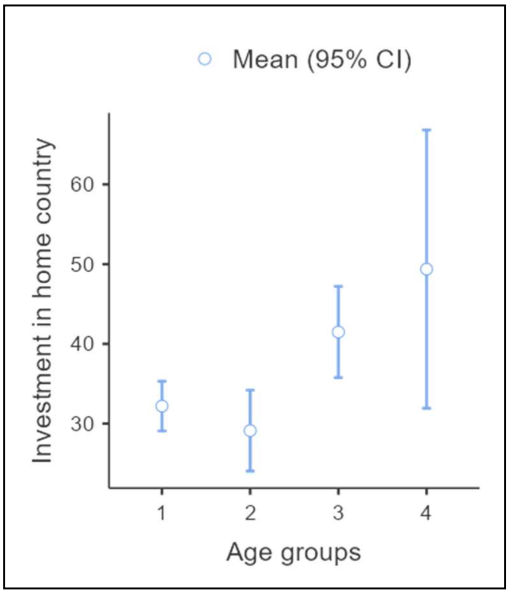
3.2.7 Impact of demographic characteristics

To evaluate if the percentage participants invested in their home country was influenced by the participants' demographic characteristics, statistical tests were conducted, as described in chapter 4.5. The Jamovi tables for these tests can be found in the appendix 2.6.

These statistical tests found that there are no significant differences in the percentage invested in the participants' home countries in terms of gender (p = 0.132), home country (p = 0.177), education (p = 0.369), investment experience (p = 0.239) or years of investment experience (p = 0.335).

However, there is a significant difference in the percentage that participants invested in stocks and additional financial products from their home country in terms of age groups (p = 0.004). When looking at the descriptives, the mean of percentage that participants from the age group 18 – 25 years invested in their home country is 32.2%, that of the group 26 – 40 years is 29.1%, that of the group 41 – 60 years is 41.5% and that of the group more than 60 years is 49.4%. Figure 12 displays these mean values along with the standard deviation.

Figure 12. *Investment in home country* by age groups



Source: Own representation

However, it is important to consider that the group sizes between the different age groups vary considerably. These differences could influence the validity of these results.

With the presentation of the empirical research results completed, the subsequent chapter focuses on the discussion of these findings alongside the results of the literature review.

4 Discussion

The discussion begins with a summary of the results of the literature review. Following this, the empirical findings are interpreted and the research questions are addressed. Finally, the limitations of this study are briefly outlined, followed by the conclusion and outlook.

4.1 Summary of the literature review

The objective of the literature review was to explore existing research concerning the influence of Robo-advisors on investors' home bias as well as the role of nudging within this context. A few studies have already explored this effect and demonstrated that Robo-advisors are able to significantly reduce investors’ home biases, though not eliminate them entirely. Similar findings have been observed for other behavioral biases. Various studies have found that Robo-advisors can significantly reduce these biases, although they do not entirely eliminate them.

Regarding the more specific question of the role of nudging, it is worth noting that nudging is feasible with Robo-advisors and is already being implemented. However, there is still no extensive existing research on how this can effectively reduce home bias. Nevertheless, while research in this specific area is limited, there are several findings indicating its potential efficacy in mitigating other behavioral biases, such as decision inertia. Existing literature suggests that nudges that not requiring an active decision from the investor are more effective in reducing investors' behavioral biases. However, it should be noted that this passive investment approach may carry other risks, such as reduced motivation to acquire financial knowledge and resulting detachment from the stock market (Lisauskiene & Darskuviene, 2021).

Based on existing literature, it can be concluded that under the right conditions and proper implementation, nudging with Robo-advisors does have the potential to reduce behavioral biases in investors. However, due to a lack of previous studies on this topic, it cannot yet be stated whether this applies to all types of behavioral biases, including home bias. Therefore, the empirical phase of this study was dedicated to further investigating this matter.

4.2 Interpretation of empirical results and answer of research questions

Since this aspect remains unexplored in existing literature, the primary goal of the empirical segment of this study was to evaluate how nudging within the framework of Robo-advisors, influences investors' home bias. To accomplish this, it is crucial to analyze initially whether and to what extent the allocation percentages of participants in stocks and other financial products indicate a bias toward their home country.

Upon reviewing the descriptive results across all groups, the mean of the percentage invested in stocks and other financial products from the participants' home country is 34.8%. Considering that the majority of participants are from Germany, Spain, France and Ireland and neither of these countries' share in the global GDP is nearly as high as 34.8%, this strongly suggests the existence of home bias. For example, Germany accounts for around 3% of the global GDP, France around 2%, Spain around 1.5% and Ireland less than 1% (IMF, 2023). Moreover, in the empirical research, there were no significant differences in the percentage participants allocated to domestic investment opportunities between countries, even though they account for a different percentage in the global GDP.

When focusing solely on stocks, within this sample, investors chose to invest only about twice as much in foreign stocks compared to what they invested in stocks from their home country. However, none of the mentioned countries accounts for such a large share of the MSCI World Index. France's weight in the MSCI World is 3.2%, while all other mentioned countries have even lower weights (MSCI World Index, 2024).

As mentioned in the chapters before, significant differences were observed between the eight groups based on whether participants were exposed to the recommendation of the Robo-advisor, the default values, the warning message, two of the above or all three. However, even within these variations, the two lowest means of the percentage invested in the participants' home countries remain as high as 21.7% (*default values* and *warning message*) and 24.5% (all three treatments). These percentages are noticeably higher than the percentage set for the Robo-advisor and the default values (10%). Moreover, when considering the percentage share of participants' home countries in the global GDP, these percentages still exceed the share of any of the main countries. This indicates a persistent presence of home bias despite the implementation of Robo-advisor recommendations and nudging techniques.

This leads to the question of how we can address the first two research questions:

RQ1: Does a recommendation from a Robo-advisor positively influence the reduction of investors' home biases?

RQ2: Does nudging positively influence the reduction of investors' home bias?

The conducted statistical test (factorial ANOVA) revealed a significant difference among the different groups and demonstrated a positive effect of all three treatments. The means in the percentage invested in stocks or other financial products of the participants' home countries were significantly reduced, suggesting a decrease in home biases. These results imply that both Robo-advisors and nudges can contribute to reduce investors' home bias.

Consequently, only the final research question remains:

RQ3: Does the nudge "warning message" or the nudge "default values" prove to be more effective in decreasing investors' home bias?

When comparing the effectiveness of nudges, the empirical results suggest that default values are more effective in overcoming home bias than warning messages. Moreover, in the context of Robo-advisors, default values additionally showed a highly significant interaction with the recommendation from the Robo-advisor, that had a notably stronger effect than the interaction between the warning message and the recommendation from the Robo-advisor. These findings favor nudges with a more passive approach (default values) over those with an active approach (warning message).

However, it's noteworthy that not all participants were aware of the warning message. Those who were aware invested significantly less in their home country—although still more than participants exposed to default values. Regarding default values, the trend was reversed: those who were unaware invested significantly less in their home country than those who were aware. These results suggest that warning messages work better when investors are aware of them, whereas default values might achieve better results when investors do not notice them.

4.3 Limitations of the empirical results

This study also faces several limitations that are worth a mention. First, the scenarios used in the experiment are simplified and do not match the complexity of the real world. The answers participants gave might not fully align with their actions in real-life situations. Moreover, in contrast to the limited information provided to participants in this experiment, serious investors are likely to access more detailed information during their investment decisions through sources such as the internet (Bhandari et al., 2008).

Another limitation is that participants were asked to make investment decisions with hypothetical money in the scenarios provided. However, numerous significant studies in finance and information systems have requested participants to consider fictional scenarios (Bhandari et al., 2008). For instance, the asset allocation decisions examined by Benartzi and Thaler (2001) also revolved around a hypothetical scenario. Furthermore, research on judgment biases has revealed that hypothetical choices made by participants correspond to real-world behavior (Kühberger et al., 2002).

Moreover, participants did not engage with an actual Robo-advisor but only received recommendations from one, which presents one of the main limitations of this study. Their behavior might have differed if they had interacted directly with a Robo-advisor. Additionally, this resulted in both the recommendation of the Robo-advisor as well as the default values not being personalized to the participants' risk profiles and home countries. As a result, these values did not necessarily reflect an optimal allocation. Participants could have potentially made different investment decisions if these values had been personalized to their specific circumstances.

Lastly, the participants of the questionnaire were primarily recruited through personal contacts of the author and director. This led to a disproportionate representation of participants in the age group 18 – 25 years (53.0%), which is relevant as a significant difference was found between age groups in the proportion of participants investing in their home country. Furthermore, the majority of participants were from Germany (73.9%), which makes the transfer of the results to other countries less reliable.

Due to these limitations, it remains uncertain whether the findings of this study can be generalized and applied to existing Robo-advisory services, necessitating future studies.

These future directions for research will be presented in the next chapter following the conclusion.

4.4 Conclusion and outlook

The objective of this study was to examine the influence of Robo-advisors on investors' home bias and the role of nudging within this framework.

Both the existing literature and the empirical evidence gathered indicate that while Robo-advisors have the potential to mitigate home bias, they do not entirely eliminate it. Similarly, concerning nudging within the context of Robo-advisors, the findings from empirical research on home bias mirror those of studies focusing on other behavioral biases: namely, that biases can be reduced but not eradicated.

Regarding the comparison between passive and active nudging approaches, the empirical findings on home bias align with those of Jung and Weinhardt (2018) regarding decision inertia. Both their research and the empirical results from this study suggest that default values, which require minimal active decision-making from investors, are more effective than warning messages, which necessitate active decision-making.

However, it is crucial to acknowledge that the passive investment approach may introduce other risks, such as diminishing motivation to acquire financial knowledge and potential detachment from the stock market (Lisauskiene & Darskuviene, 2021).

Given the limitations of this empirical study, further research on this topic is necessary for a more comprehensive understanding. Future studies should consider conducting laboratory or field experiments incorporating an actual Robo-advisor and personalized recommendations and default values. These approaches would improve the reliability of the results and provide greater insight into how applicable they are to real-world Robo-advisory services.

Furthermore, including participants from a wider range of home countries and diverse age groups in future studies would be beneficial, enhancing the reliability of the findings. Including diverse age groups would also help confirm the results of the current study regarding variations in the level of home bias across different age groups.

Moreover, exploring different nudging techniques beyond warning messages and default values could offer valuable insights into potentially more effective strategies. Additionally, future studies could extend this work by investigating personalized nudging techniques and their efficacy in reducing home bias. Testing various nudges would enhance our understanding of their influence on investor behavior and help identify the most effective approaches for reducing home biases.

Consequently, insights gained from future studies will have a significant impact on both the theoretical foundations and the practical aspects of investment decisions.

Declaration of use of generative artificial intelligence tools in bachelor's thesis

WARNING: At the University, we consider ChatGPT or similar tools to be very useful in academic life, although their use always remains the responsibility of the student, as the responses they provide may not be accurate. In this regard, its use in the development of the Bachelor's Thesis to generate code is NOT permitted because these tools are not reliable for that task. Even if the code works, there are no guarantees that it is methodologically correct, and it is highly likely that it is not.

Hereby, I, Mara Schneider, a student of *Administración y Dirección de Empresas con Mención Internacional* at the *Universidad Pontificia Comillas*, presenting my Bachelor's Thesis entitled "What influence does nudging have on the home bias of investors in the context of Robo-advisors?", declare that I have used the generative Artificial Intelligence tool ChatGPT or similar AI tools for code only in the context of the activities described below [the student must keep only those activities in which ChatGPT or similar tools have been used and delete the rest. If none have been used, delete all and write "I have not used any"]:

1. **Literary and language style corrector:** To improve the linguistic and stylistic quality of the text.
2. **Translator:** To translate texts from one language to another.

I affirm that all the information and content presented in this work are the product of my research and individual effort, except where indicated otherwise and appropriate credits have been given (I have included the proper references in the Bachelor's Thesis and have explained for what ChatGPT or similar tools have been used). I am aware of the academic and ethical implications of presenting non-original work and accept the consequences of any violation of this declaration.

Date: 08/03/2024

Signature: M. Schneider

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Appendix

Appendix 1: Questionnaire

------------------------------------Begin of the questionnaire------------------------------------

Hello everybody - I am currently working on my bachelor's thesis and would greatly appreciate it if you could spare a few minutes to complete this survey. It won't take much longer than 1 minute (I promise!) and would be immensely helpful to me.

Thank you for participating,

Mara

Participation & data protection:

This survey will be handled entirely anonymously. The collected data will only be accessible to the researcher of the study, who will always process them anonymously. The data provided by participants will not be used for any other purpose than this study. At no time will any identity be investigated or revealed.

Your participation in the research is entirely voluntary, and you can decide to discontinue it at any time.

The entire research process will be conducted ensuring the anonymity of the participants and the voluntary nature of participation.

Requirements to participate:

1. Be at least 18 years old.
2. If you need any clarification, you can contact the researcher of this study: Mara Schneider: marasofia.schneider@gmail.com

Clicking the "YES, I agree to participate in the study" button implies that:

a. I have read and understood all the information regarding participation in the study.
b. I know who to contact if I have any doubts about the study.
c. I am aware that the data will be handled entirely anonymously, and its confidentiality will be maintained.
d. I voluntarily consent to participate in this study and am aware that I am free to withdraw at any time without having to provide any explanation.
e. I am over 18 years old.

Clicking "Yes" implies agreeing to participate in the survey.

- Yes

---Page change---

On which day of the month were you born?
Example: If your birthday is on the 27th of August, select the option "24-27"

- 1-4 *(Group 1)*
- 5-8 *(Group 2)*
- 9-13 *(Group 3)*
- 14-16 *(Group 4)*
- 17-20 *(Group 5)*
- 21-23 *(Group 6)*
- 24-27 *(Group 7)*
- 28-31 *(Group 8)*

---Page change---

Group 1 – 4:

Imagine you a have significant amount of money to invest. How would you allocate this money (in %) among the following investment options? Indicate the allocation in the fields below. Please make sure that the total amount equals 100%.

Stocks from your own country:
_____[free space]______ *[default value: 5]*

Stocks from other countries:
_____[free space]______ *[default value: 45]*

Additional financial products from your home country:
_____[free space]______ *[default value: 5]*

Additional financial products from other countries:
_____[free space]______ *[default value: 45]*

Note: for group 3 & 4 the free spaces were pre-completed with the default values indicated above.

Group 5 – 8:

Imagine you a have significant amount of money to invest.

Also imagine you're using a Robo-advisor. (Robo-advisors are digital platforms that use algorithms to provide users with automated investment advice.)

It suggests the following allocation:

Stocks from your home country: 5%
Stocks from other countries: 45%

Additional financial products from your home country: 5%
Additional financial products from other countries: 45%
Considering this information, how would you allocate the money (in %) among the following investment options? Indicate the allocation in the fields below. Please make sure that the total amount equals 100%.

Stocks from your own country:
_____[free space]______ *[default value: 5]*

Stocks from other countries:
_____[free space]______ *[default value: 45]*

Additional financial products from your home country:
_____[free space]______ *[default value: 5]*

Additional financial products from other countries:
_____[free space]______ *[default value: 45]*

Note: for group 7 & 8 the free spaces were pre-completed with the default values indicated above.

---Page change--

Group 2, 4, 6 & 8:

Warning

Many investors are prone to home bias. That means they invest a disproportionate amount in stocks and other financial products from their home country. Home bias has a negative effect on a portfolio's performance. If this information entices you to change your investment decision, feel free to go back to the last section and change your answer.

---Page change--

From here on: all groups

Where are you from?

- Germany
- Spain
- France
- Ireland
- Other: [free space]

In the question regarding the allocation/ your investment decision, were the responses already filled out before you entered anything?

- Yes
- No

What gender do you identify with?

- Male
- Female
- Other
- Prefer not to say

If you are reading this question, select "3".

- 1
- 2
- 3

What is the highest level of education you have completed or the highest degree you have received?

- Less than high school degree
- High school degree or equivalent
- Bachelor's degree or equivalent
- Master’s degree or equivalent
- More than Master’s degree (PhD etc.)
- Other: [free space]

Did a warning message appear at any point during the questionnaire?

- Yes
- No

Which statement describes your investment history best?

- I have never invested in stocks or other financial products.
- I have already invested or am currently investing in stocks or other financial products.

--Page change--

If participant indicated that they had already invested:

For how many years have you been investing in stocks or other financial products?

- Less than 2 years
- 2 – 5 years
- 6 – 10 years
- 11 – 20 years
- More than 20 years

--Page change--

Thank you so much for your participation!

You can now hit “Send”.

-----------------------------------End of the questionnaire-------------------------------------

Appendix 2: Statistical tests

Appendix 2.1: Description of Sample and size of groups

Home country (0= Germany, 1= Spain, 2= France, 3= Ireland, 4= other countries)

Home country	Counts	% of Total	Cumulative %
0	290	73.2 %	73.2 %
1	55	13.9 %	87.1 %
4	10	2.5 %	89.6 %
2	27	6.8 %	96.5 %
3	14	3.5 %	100.0 %

Education (1= high school, 2= vocational training or similar, 3= bachelor's degree, 4= master's degree, 5= more than master's degree)

Education	Counts	% of Total	Cumulative %
3	92	23.2 %	23.2 %
1	233	58.8 %	82.1 %
4	58	14.6 %	96.7 %
5	7	1.8 %	98.5 %
2	6	1.5 %	100.0 %

Investment experience (0= never invested before, 1= invested before)

Investment experience	Counts	% of Total	Cumulative %
1	228	57.6 %	57.6 %
0	168	42.4 %	100.0 %

Years of investment experience (1= less than two years, 2= 2 – 5 years, 3= 6 – 10 years, 4= 11- 20 years, 5= more than 20 years)

Years of investment experience	Counts	% of Total	Cumulative %
4	36	15.9 %	15.9 %
2	71	31.3 %	47.1 %
3	23	10.1 %	57.3 %
1	67	29.5 %	86.8 %
5	30	13.2 %	100.0 %

Age groups (1= 18 – 25 years, 2= 26 – 40 years, 3= 41 – 60 years, 4 = more than 60 years)

Age groups	Counts	% of Total	Cumulative %
1	210	53.0 %	53.0 %
2	68	17.2 %	70.2 %
3	102	25.8 %	96.0 %
4	16	4.0 %	100.0 %

Gender (0= male, 1= female)

Gender	Counts	% of Total	Cumulative %
0	170	42.9 %	42.9 %
1	226	57.1 %	100.0 %

Group size

Group	Counts	% of Total	Cumulative %
1	51	12.9 %	12.9 %
2	47	11.9 %	24.7 %
3	53	13.4 %	38.1 %
4	49	12.4 %	50.5 %
5	51	12.9 %	63.4 %
6	50	12.6 %	76.0 %
7	51	12.9 %	88.9 %
8	44	11.1 %	100.0 %

Appendix 2.2: Equivalence of groups

Equivalence of groups in terms of age groups

Contingency Tables

	Age groups				
Group	1	2	3	4	Total
1	28	4	14	5	51
2	27	10	9	1	47
3	29	7	14	3	53
4	21	11	15	2	49
5	25	13	12	1	51
6	28	9	12	1	50
7	26	8	16	1	51
8	26	6	10	2	44
Total	210	68	102	16	396

χ^2 Tests

	Value	df	p
χ^2	17.4	21	0.686
N	396		

Equivalence of groups in terms of home countries

	Home country					
Group	0	1	4	2	3	Total
1	42	5	1	2	1	51
2	32	7	1	3	4	47
3	43	5	1	3	1	53
4	35	7	1	5	1	49
5	34	11	0	5	1	51
6	29	10	2	5	4	50
7	42	3	2	3	1	51
8	33	7	2	1	1	44
Total	290	55	10	27	14	396

χ^2 Tests

	Value	df	p
χ^2	26.6	28	0.538
N	396		

Equivalence of groups in terms of level of education

	Education					
Group	3	1	4	5	2	Total
1	10	34	6	1	0	51
2	9	30	6	0	2	47
3	12	33	7	1	0	53
4	14	21	12	1	1	49
5	15	30	5	0	1	51
6	16	26	6	2	0	50
7	8	30	10	2	1	51
8	8	29	6	0	1	44
Total	92	233	58	7	6	396

χ^2 Tests

	Value	df	p
χ^2	25.2	28	0.617
N	396		

Equivalence of groups in terms of gender

Contingency Tables

	Gender		
Group	0	1	Total
1	22	29	51
2	23	24	47
3	22	31	53
4	24	25	49
5	20	31	51
6	20	30	50
7	24	27	51
8	15	29	44
Total	170	226	396

χ^2 Tests

	Value	df	p
χ^2	3.69	7	0.815
N	396		

Equivalence of groups in terms of investment experience

Contingency Tables

	Investment experience		
Group	1	0	Total
1	27	24	51
2	25	22	47
3	30	23	53
4	37	12	49
5	30	21	51
6	25	25	50
7	33	18	51
8	21	23	44
Total	228	168	396

χ^2 Tests

	Value	df	p
$\chi^{2\ 2}$	11.3	7	0.126
N	396		

Equivalence of groups in terms of years of investment experience

Contingency Tables

	Years of investment experience					
Group	4	2	3	1	5	Total
1	4	7	4	10	2	27
2	3	9	4	6	3	25
3	7	10	3	7	3	30
4	8	15	3	6	4	36
5	5	9	1	9	6	30
6	2	10	4	7	2	25
7	7	5	2	14	5	33
8	0	6	2	8	5	21
Total	36	71	23	67	30	227

χ^2 Tests

	Value	df	p
χ^2	26.7	28	0.536
N	227		

Appendix 2.3: Descriptive results across all groups

Descriptives across all groups

	Investment in home country
N	396
Missing	0
Mean	34.8
Median	30.0
Standard deviation	25.3
Minimum	0
Maximum	100

Descriptives across all groups

	"Stocks from your home country"	"Stocks from other countries"	"Additional financial products from your home country"	"Additional financial products from other countries"
N	396	396	396	396
Missing	0	0	0	0
Mean	19.5	36.2	15.3	29.1
Median	15.0	40.0	10.0	30.0
Standard deviation	18.0	19.3	15.2	19.8
Minimum	0.00	0.00	0.00	0.00
Maximum	100	100	100	100

Appendix 2.4: Descriptives on investment in home country

Descriptives all treatments (0= treatment not active, 1= treatment active)

	Default values	Robo-advisor	Warning message	Investment in home country
Mean	0	0	0	63.9
			1	44.4
		1	0	38.0
			1	31.5
	1	0	0	27.9
			1	21.7
		1	0	25.1
			1	24.5
Median	0	0	0	70
			1	40
		1	0	35
			1	30.0
	1	0	0	25
			1	15
		1	0	15
			1	10.0
Standard deviation	0	0	0	24.9
			1	24.3
		1	0	22.3
			1	18.6
	1	0	0	19.3
			1	19.9
		1	0	22.3
			1	21.9

Descriptives warning message (0= no warning message, 1= warning message)

	Warning message	**Investment in home country**
N	0	206
	1	190
Mean	0	38.6
	1	30.5
Median	0	35.0
	1	26.0
Standard deviation	0	26.9
	1	22.8

Descriptives default values (0= no default values, 1= default values)

	Default values	Investment in home country
N	0	199
	1	197
Mean	0	44.5
	1	24.9
Median	0	40
	1	20
Standard deviation	0	25.6
	1	20.8

Descriptives Robo-advisor (0= no Robo-advisor, 1= Robo-advisor)

	Robo-advisor	Investment in home country
N	0	200
	1	196
Mean	0	39.5
	1	30.0
Median	0	35.0
	1	25.0
Standard deviation	0	27.5
	1	21.9

Appendix 2.5: Factorial ANOVA and Post Hoc Tests

ANOVA - Investment in home country

	Sum of Squares	df	Mean Square	F	p	η^2p
Default values	38081	1	38081	80.369	< .001	0.172
Robo-advisor	9309	1	9309	19.647	< .001	0.048
Warning message	6689	1	6689	14.117	< .001	0.035
Default values ✻ Robo-advisor	9211	1	9211	19.440	< .001	0.048
Default values ✻ Warning message	2291	1	2291	4.834	0.028	0.012
Robo-advisor ✻ Warning message	2136	1	2136	4.508	0.034	0.011
Default values ✻ Robo-advisor ✻ Warning message	341	1	341	0.719	0.397	0.002
Residuals	183847	388	474			

Homogeneity of Variances Test (Levene's)

F	df1	df2	p
1.29	7	388	0.256

Normality Test (Shapiro-Wilk)

Statistic	p
0.939	< .001

Post Hoc Comparison - Default values (0= no default values, 1= default values)

Comparison							
Default values		Default values	Mean Difference	SE	df	t	p_{tukey}
0	-	1	19.6	2.19	388	8.96	< .001

Note. Comparisons are based on estimated marginal means

Post Hoc Comparison - Warning message (0= no warning message, 1= warning message)

Comparison							
Warning message		Warning message	Mean Difference	SE	df	t	p_{tukey}
0	-	1	8.23	2.19	388	3.76	< .001

Post Hoc Comparison - Robo-advisor (0= no Robo-advisor, 1= Robo-advisor)

Comparison							
Robo-advisor		Robo-advisor	Mean Difference	SE	df	t	p_{tukey}
0	-	1	9.71	2.19	388	4.43	< .001

Note. Comparisons are based on estimated marginal means

Post Hoc Comparison - Default values ✻ Robo-advisor (0= treatment not active, 1= treatment active)

Comparison									
Default values	Robo-advisor		Default values	Robo-advisor	Mean Difference	SE	df	t	p_{tukey}
0	0	-	0	1	19.3720	3.09	8	6.2736	< .001
		-	1	0	29.3026	3.08	388	9.5092	< .001
		-	1	1	29.3540	3.14	388	9.3491	< .001
	1	-	1	0	9.9306	3.06	388	3.2486	0.007
		-	1	1	9.9820	3.12	388	3.2039	0.008
1	0	-	1	1	0.0514	3.11	388	0.0165	1.000

Note. Comparisons are based on estimated marginal means

Post Hoc Comparison - Default values ✻ Warning message (0= treatment not active, 1= treatment active)

Comparison									
Default values	Warning message		Default values	Warning message	Mean Difference	SE	df	t	p_{tukey}
0	0	-	0	1	13.05	3.09	388	4.23	< .001
		-	1	0	24.46	3.03	388	8.06	< .001
		-	1	1	27.87	3.12	388	8.92	< .001
	1	-	1	0	11.41	3.07	388	3.71	0.001
		-	1	1	14.82	3.16	388	4.69	< .001
1	0	-	1	1	3.41	3.11	388	1.10	0.691

Note. Comparisons are based on estimated marginal means

Estimated Marginal Means - Default values ✻ Robo-advisor (0= treatment not active, 1= treatment active)

				95% Confidence Interval	
Robo-advisor	Default values	Mean	SE	Lower	Upper
0	0	54.1	2.20	49.8	58.5
	1	24.8	2.16	20.6	29.1
1	0	34.8	2.17	30.5	39.0
	1	24.8	2.24	20.4	29.2

Estimated Marginal Means - Default values ✻ Warning message (0= treatment not active, 1= treatment active)

				95% Confidence Interval	
Warning message	Default values	Mean	SE	Lower	Upper
0	0	51.0	2.16	46.7	55.2
	1	26.5	2.13	22.3	30.7
1	0	37.9	2.21	33.6	42.3
	1	23.1	2.26	18.7	27.6

Estimated Marginal Means - Warning message ✻ Robo-advisor (0= treatment not active, 1= treatment active)

				95% Confidence Interval	
Robo-advisor	Warning message	Mean	SE	Lower	Upper
0	0	45.9	2.13	41.7	50.1
	1	33.0	2.22	28.7	37.4
1	0	31.6	2.16	27.3	35.8
	1	28.0	2.25	23.6	32.4

Appendix 2.6: Additional ANOVAs and Independent Samples T-Tests

Differences in investment in home country between participants with investment experience and participants without

Independent Samples T-Test

		Statistic	p
Investment in home country	Mann-Whitney U	17833	0.239

Normality Test (Shapiro-Wilk)

	W	p
Investment in home country	0.916	< .001

Note. A low p-value suggests a violation of the assumption of normality

Homogeneity of Variances Test (Levene's)

	F	df	df2	p
Investment in home country	0.0287	1	394	0.866

Note. A low p-value suggests a violation of the assumption of equal variances

Group Descriptives

	Group	N	Mean	Median	SD	SE
Investment in home country	1	228	33.7	30.0	25.5	1.69
	0	168	36.2	30.0	25.0	1.93

Differences in investment in home country in terms of level of education

Kruskal-Wallis

	χ^2	df	p
Investment in home country	4.28	4	0.369

Differences in investment in home country in terms of home country

Kruskal-Wallis

	χ^2	df	p
Investment in home country	6.32	4	0.177

Differences in investment in home country in terms of gender

Independent Samples T-Test

		Statistic	p
Investment in home country	Mann-Whitney U	17523	0.132

Normality Test (Shapiro-Wilk)

	W	p
Investment in home country	0.919	< .001

Note. A low p-value suggests a violation of the assumption of normality

Homogeneity of Variances Test (Levene's)

	F	df	df2	p
Investment in home country	2.46	1	394	0.117

Note. A low p-value suggests a violation of the assumption of equal variances

Group Descriptives

	Group	N	Mean	Median	SD	SE
Investment in home country	0	170	32.3	30.0	24.0	1.84
	1	226	36.6	30.0	26.1	1.74

Differences in investment in home country in terms of years of investment experience

Kruskal-Wallis

	χ^2	df	p
Investment in home country	4.57	4	0.335

Differences in investment in home country in terms of age groups

One-Way ANOVA (Welch's)

	F	df1	df2	p
Investment in home country	4.92	3	62.2	0.004

Group Descriptives

	Age groups	N	Mean	SD	SE
Investment in home country	1	210	32.2	22.9	1.58
	2	68	29.1	21.0	2.54
	3	102	41.5	29.1	2.88
	4	16	49.4	32.8	8.19

Homogeneity of Variances Test (Levene's)

	F	df1	df2	p
Investment in home country	5.65	3	392	< .001

Appendix 2.7: Differences in manipulation checks

Differences in investment in home country between groups "aware of warning message" and "not aware of warning message"

Independent Samples T-Test

		Statistic	p	Mean difference	SE difference
Investment in home country	Mann-Whitney U	1967	0.001	-15.0	

Normality Test (Shapiro-Wilk)

	W	p
Investment in home country	0.939	< .001

Note. A low p-value suggests a violation of the assumption of normality

Homogeneity of Variances Test (Levene's)

	F	df	df2	p
Investment in home country	18.6	1	188	< .001

Note. A low p-value suggests a violation of the assumption of equal variances

Group Descriptives (0= not aware of warning message, 1= aware of warning message)

	Group	N	Mean	Median	SD	SE
Investment in home country	1	151	26.9	25.0	19.0	1.54
	0	39	44.5	40.0	30.2	4.83

Differences in investment in home country between groups "aware of default values" and "not aware of default values"

Independent Samples T-Test

		Statistic	p	Mean difference	SE difference
Investment in home country	Mann-Whitney U	576	0.002	-10.00	

Normality Test (Shapiro-Wilk)

	W	p
Investment in home country	0.862	< .001

Note. A low p-value suggests a violation of the assumption of normality

Homogeneity of Variances Test (Levene's)

	F	df	df2	p
Investment in home country	6.31	1	195	0.013

Note. A low p-value suggests a violation of the assumption of equal variances

Group Descriptives

	Group	N	Mean	Median	SD	SE
Investment in home country	0	13	10.8	10.0	11.4	3.17
	1	184	25.9	20.0	21.0	1.55