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Nudge and sustainable finance:

Promoting Socially Responsible Investments through choice architecture

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INTRODUCTION

Nowadays, sustainability is getting more and more attention from both institutions and citizens. In recent decades, climate change has become one of the main issues that mankind is going to face. For this reason, the United Nations has recently adopted the 2030 Agenda for Sustainable Development, a program composed of 17 goals aimed at encouraging actions and processes that lead societies and human beings to a sustainable lifestyle. Sustainable development could be defined as "the development that meets the needs of the present without compromising the ability of future generations" (Brutland Commission, 1987, p. 54). Within this framework, the concept of development has shifted its focus from a mere economic point of view to a broader meaning that considers also other factors.

The sustainable development framework has meant greater focus on the role of business in achieving sustainability, with the concept of corporate social responsibility gaining popularity. Indeed, besides financial performance, the ethical and environmental commitment of companies is getting more and more attention nowadays. Therefore, ESG criteria were created to evaluate corporates impact on environmental (E), social (S), and governance (G) domains. These ratings are frequently used as screening criteria for the development of socially responsible investment (SRI) products, thus helping to include only those companies that meet strong ethical and sustainability standards (Camilleri, 2021). Socially responsible investing refers to a financial strategy that combines both financial performance and social responsibility in the investment decision-making process (Martini, 2021). In doing so, investors can obtain economic profits in accordance with their ethical, prosocial, and pro-environmental values. This kind of investments thus combine economic profits with an ethical dimension and, consequently, they might be an alternative way to actively engage private investors in the sustainable development process (Gutsche & Zwergel, 2020) or to attract potential investors and promote financial market participation (Rossi et al., 2019).

The market for SRI has increasingly captured the interest of institutional and private investors in the last two decades and the value of SRI portfolios has grown as well (Widyawati, 2020). According to the Global Sustainable Investment Alliance (Global Sustainable Investment Alliance, 2020), in 2020 sustainable investment products under management accounted for 35.9% of the total managed funds. As reported by Bloomberg (2021), in 2020 the global ESG assets reported a 15% increase from 2018, reaching a value of over $35 trillion. The value for SRI is expected to grow up to $50 trillion by 2025, hence representing one-third of the total assets under management globally. This growth is, on fact, breaking the assumptions of the modern portfolio theory (Markowitz, 1952), according to which investors would behave rationally and take their decisions only considering risk-return trade-offs and expected performances of their investments, with the only purpose of profit maximization (Bauer & Smeets, 2015). Conversely, there is evidence that investors are not necessarily wealth-maximizers and profit-oriented (Gamel et al., 2016; Jonwall et al., 2023a). Instead of focusing merely on the return on investments, as expected by classical financial theories, socially responsible investors would consider both financial (e.g., the performance or the riskiness of specific assets) and non-financial decision criteria, such as values, beliefs, and attitudes, in their investment decisions (Bauer & Smeets, 2015; Nakai et al., 2018; Pilaj, 2017).

Literature on SRI has parallel grown in recent years, with a specific focus on comparing the financial performance of SRI to that of conventional financial assets (Beloskar et al., 2023).

A second topic of interest concerns the reliability of ESG ratings. Indeed, as stated by recent studies (Widyawati, 2020; Gangi et al., 2022) ESG criteria show two main issues: a lack of transparency and a lack of convergent validity among various ratings. This matter could also have negative effects on investors' attitudes and trust toward socially responsible investing. For instance, ESG rating uncertainty, due to the lack of standardized rating criteria, might reduce investors' demand for SRI products (Avramov et al., 2022). In this direction, a recent research field involves the issue of greenwashing, focusing on both companies greenwashing behaviors (e.g., Yu et al., 2020) and the development of strategies aimed at preventing greenwashing, such as the definition of clear and standardized ESG ratings to evaluate corporate social responsibility (Arvidsson & Dumay, 2022). Without standardized ESG disclosure rules, companies could manipulate the narrative by selectively highlighting positive information while omitting negative details to create an overly favorable image. This practice can potentially lead to overstated environmental benefits. As a result, it becomes challenging for stakeholders to assess firms' transparency and ESG performance, as the available data is self-reported, often unchecked, and unaudited for reliability by independent verifiers (Kapil & Rawal, 2023).

Though literature on SRI is getting more and more rich, little attention has been paid so far on the motivations and drivers of private investors' decision to invest in sustainable financial assets (Garg et al., 2022). Indeed, previous studies mostly attempted to identify the profile of socially responsible investors focusing on socio-demographic characteristics, such as gender, age, and education (e.g., Cheah et al., 2011; Junkus & Berry, 2010). However, some authors (Dorfleitner & Utz, 2014; Nilsson, 2009; Wins & Zwergel, 2016) suggest that socio-demographic variables, alone, cannot fully describe the socially responsible investors' profile, as they have less explanatory power than attitudinal and psychological variables.

To date, only few studies investigated the role of psychological characteristics in sustainable investment decisions. Therefore, a better understanding of the determinants that shape socially responsible investing is needed. Deepening the characteristics of those investing in SRI could have relevant implications. Investigating the psychological determinants of socially responsible investing could help to better understand the factors that come into play in the decision-making process towards sustainable investing or, conversely, to identify the barriers that prevent it. Moreover, further research on the topic could help to identify those consumers attracted by the idea of investing in socially responsible assets and to target them with specific investment products suited to investors' ethical values, attitudes, and preferences (Brunen & Laubach, 2022).

Starting from this gap in literature, the present doctoral project has a twofold objective. First, it aims to investigate the psychological characteristics that may influence consumers' decisions to engage in socially responsible investing. These characteristics include attitudes, motivations, and perceived barriers that may either facilitate or hinder individuals from choosing sustainable financial assets. By identifying these factors, this research seeks to uncover the underlying psychological mechanisms that shape the investment decision-making process related to SRI. Second, based on the insights gained from the exploratory studies of the project, a series of behavioral interventions - commonly referred to as nudges - were developed to encourage socially responsible investing. Nudges are subtle and non-coercive strategies derived from behavioral economics, designed to influence behavior by changing the choice architecture of a specific contest, without restricting freedom of choice. Therefore, the overall goal of this project is not only to deepen our understanding of the determinants of SRI, but also to provide actionable strategies to promote sustainable financial behaviors among consumers.

The present work is deeply grounded in the framework of behavioral economics, which departs from traditional economic models assuming individuals as perfectly rational decision-makers. Instead, behavioral economics assumes that real-world decisions are often influenced by cognitive biases and emotional factors. In the context of SRI, it is particularly important to explore how psychological variables, such as ethical values and personal beliefs, interact with financial decision criteria, given that SRI represent a complex blend of financial and ethical decision making.

The structure of this dissertation follows a logical progression, designed to build a comprehensive understanding of socially responsible investing from a behavioral perspective. The first chapter will present an empirical study [1], which is currently under review, aimed at exploring the role of traditional financial decision-making variables in shaping sustainable investment intentions. This chapter demonstrates that while these factors are important in conventional investing, they may not fully explain the decision to invest in SRI. The study thus highlights the need for a broader framework that also accounts for non-financial factors, such as personal values and attitudes.

Chapter 2 focuses instead on the Italian adaptation of the GREEN scale, a psychometric instrument measuring personal values towards environmental sustainability. By embracing the contemporary view of validity framework (Hubley & Zumbo, 2011; Peeters & Harpe, 2020), the construct validity of the scale was proved also in the Italian context by collecting different validity evidence. This work is closely connected to the broader aims of the doctoral project, as the GREEN scale will serve as a measure in the following study. The chapter is retrieved from a paper [2] published in the journal *TPM – Testing, Psychometrics, and Methodology in Applied Psychology*.

Then, Chapter 3 expands on the findings presented in Chapter 1 by proposing a theoretical model that integrates both financial and non-financial determinants. The results from Chapter 1 suggest indeed that traditional investment decision-making models have a limited explanatory power when applied to SRI. To address this gap, a model also including psychological determinants was developed. This chapter is derived from a paper [3] already published in the journal *Frontiers in Behavioral Economics*. Chapter 4 is strictly connected with the previous chapter, since it is aimed at validating the theoretical model through machine learning algorithms. The chapter is based on a study [4] which is currently under review.

Finally, Chapter 5 reports an experimental study in which participants, placed in a simulation-based scenario, were requested to make investment decisions choosing from a pool of both conventional and ESG financial assets. The purpose of the study was to test whether "nudges" can effectively steer individuals toward more sustainable investment choices. Specifically, in this experiment, a series of nudges were designed to change the choice architecture of the scenario (i.e., a bank website) so to, consequently, affect consumers' decision-making process. Specifically, the tested nudges were designed considering the psychological and behavioral insights uncovered in literature. They are thus tailored to address the psychological barriers towards SRI.

CHAPTER 1

NOT TARRING EVERY INVESTOR WITH THE SAME BRUSH: DETERMINANTS ASSOCIATED WITH CONVENTIONAL AND SUSTAINABLE INVESTMENT DECISIONS ARE NOT NECESSARILY THE SAME

As reported in the introduction, the decision to invest in SRI involves different decision criteria (i.e., financial and ethical aspects), since both financial information and personal characteristics (e.g., personal values and attitudes) contribute to shaping investors behaviors. Hence, it could be argued that, alone, financial motives are not enough to explain consumers' socially responsible investing. Despite the growing interest in SRI, various gaps remain in understanding the psychological determinants of these decisions. Existing literature has largely focused on socio-demographic characteristics with mixed results and limited explanatory power (Jonwall et al., 2023b). While previous studies (Delsen & Lehr, 2019; Singh et al., 2021) have focused on values and attitudes shaping socially responsible investing decisions, the role of classical determinants of investment decision-making in relation to SRI remains under-researched. Addressing this gap could help determine whether classical financial determinants remain relevant in the context of SRI or if these decisions are predominantly influenced by other aspects, such as ethical values and personal attitudes.

The contribution of the present study to the literature on socially responsible investing is twofold. First, we aim to examine whether variables traditionally associated with investment decision-making (i.e., financial literacy, financial self-efficacy, risk attitudes, future orientation, and ambiguity tolerance) can also predict socially responsible investing. Secondly, we aim to assess whether these variables have the same explanatory power in predicting the intention to invest in SRI compared to the intention to invest in conventional investments. Specifically, by performing a path analysis, we estimated consumers' willingness to invest in both conventional and sustainable financial assets in a sample of Italian consumers. Furthermore, we examined whether each predictor in the model influences the decision to invest in conventional and socially responsible products differently.

1. Literature review

According to behavioral finance, many variables are enclosed in the investment decision-making process. As a consequence, to develop the theoretical model we relied on the Stimuli-Organism-Response (SOR) theory (Jacoby, 2002). This framework posits that an external stimulus triggers an internal organism response—such as personality traits, values, emotions, or attitudes—which then leads to an observable response, such as a decision or action. Hence, the decision to invest in SRI would not be solely determined by objective factors, but it would also depend on individual's cognitive and emotional responses. To define the theoretical framework, we focused on variables traditionally associated with behavioral finance and psychological sciences, prioritizing those most frequently highlighted in the literature for their influence on investment behavior. Specifically, we identified five key determinants: financial literacy, financial self-efficacy, financial risk attitude, future orientation, and ambiguity tolerance. A systematic literature review - including studies from various countries and contexts - was conducted to justify the inclusion of each variable, linking them both to traditional and sustainable investment decisions.

Financial literacy is commonly investigated in the context of financial behaviors. Defined as a combination of knowledge, skills, and attitudes required for proper financial behavior (OECD, 2013), the literature reports that financial literacy plays a significant role in investment decisions (e.g., Goyal & Kumar, 2021), as financially literate individuals are more likely to participate in financial markets (Bannier & Neubert, 2016; Robba et al., 2024a). Similarly, financial literacy shapes investors' portfolio composition and asset allocation

(Abreu & Mendes, 2010; Hermansson & Jonsson, 2021; Zhu & Xiao, 2021). Financial literacy appears to influence the decision to invest in SRI (Escrig-Olmedo et al., 2013; Raut et al., 2021). Additionally, there is evidence that individuals who possess greater knowledge specifically about socially responsible investing are more inclined to invest in sustainable financial products (Jonwall et al., 2023b; Wins & Zwergel, 2016).

Besides objective knowledge, confidence in one's own skills and capabilities is another key determinant of financial behaviors (e.g., Bannier & Schwarz, 2018; Mishra et al., 2022; Robba et al., 2024a). Forbes and Kara (2010) define financial self-efficacy as individuals' confidence and beliefs about their own financial competencies and knowledge. Evidence suggests that financial self-efficacy is also involved in investment decisions and could be a stronger predictor of financial market participation than financial literacy itself (e.g., Montford & Goldsmith, 2016).

Financial risk tolerance, or the degree of risk that investors are willing to endure in their financial decisions, is also frequently called in cause in investment decision-making. Indeed, risk appetite tends to shape both the decision to invest in financial markets and investors' asset allocation (Keller & Siegrist, 2006). However, the role of risk tolerance toward sustainable investments is still debated in the literature. Some studies found that risk appetite affects the decision to invest in socially responsible assets (Bauer & Smeets, 2015; Riedl & Smeets, 2017; Robba et al., 2024b). Conversely, other scholars reported non-significant associations between individuals' risk tolerance and their willingness to invest in SRI (Nakai et al., 2018). For instance, Delsen and Lehr (2019), in a study of Dutch pension fund participants, found that risk appetite is unable to predict the decision to invest ethically. This would suggest that this variable could be a relevant measure in conventional investment decisions, by explaining risk-return trade-off preferences, but not in socially responsible investing.

Individuals' concern for the future, namely future orientation, is another key determinant frequently investigated in financial literature, as deferring gratification and planning for the future may be difficult for some people (Xiao & Porto, 2019; Robba et al., *in press*). Present bias makes individuals more prone to seek immediate rewards rather than delay gratification for future positive outcomes (Rambaud et al., 2023). This attitude could promote financial misbehavior. On the other hand, future orientation is associated with positive financial behaviors, such as saving (Allom et al., 2018) and investing (Robba et al., 2024a; Sekścińska et al., 2021). Though the role of temporal orientation in socially responsible investing is under researched, it seems that prompting a distant-future mindset through priming strategies makes investors more likely to pay higher fees for SRI (Alexander et al., 2012).

Financial market participation involves uncertainty, as investors are often required to make choices relying on partial or incomplete information. Thus, it could be expected that ambiguity and uncertainty intolerance affect investment decision-making (Antoniou et al., 2015; Li et al., 2017; Rieger, 2022). Intolerance of uncertainty has been defined as "an individual's dispositional incapacity to endure the aversive response triggered by the perceived absence of salient, key, or sufficient information, and sustained by the associated perception of uncertainty" (Carleton, 2016, p. 31). Empirical evidence shows that individuals who are intolerant of uncertainty are less likely to participate in financial markets and tend to hold fewer stocks in their portfolios (Dimmock et al., 2016). It seems that also ambiguous contexts can shape investment decisions. For instance, Agarwal et al. (2022) found that in times of political uncertainty, investors reduce their participation in financial markets and are inclined to prefer safer financial assets. In a similar direction, Avramov et al. (2022) found that the uncertainty concerning ESG ratings, due to the lack of standardized criteria to measure companies ESG scores, can shape investors' decision-making, reducing the demand for socially responsible financial assets. Furthermore, to date there is still uncertainty regarding the financial performance of SRI. There is indeed a lack of agreement whether they over- or underperform conventional financial assets (Widyawati, 2019). This uncertainty might negatively affect the decision to invest responsibly as well.

2. The present study

The present study aims at understanding the role of variables commonly related to investment decision-making (i.e., financial literacy, financial self-efficacy, financial risk attitudes, future orientation, and ambiguity tolerance) in explaining the decision to invest ethically also controlling for socio-demographic characteristics (i.e., gender, age, and education). Furthermore, since the sample included both financial market investors and non-investors, we also accounted for investment status (i.e., whether respondents were active in financial markets or not). Specifically, relying on cross-sectional data obtained from a sample of Italian consumers, this study aims to determine whether these variables are also associated with the intention to invest in SRI (Aim 1) and whether they have less explanatory power in determining sustainable investment decisions (Aim 2). Consistent with previous findings (e.g., Riedl & Smeets, 2017), we expect that classical investment decision-making determinants contribute less to the understanding of sustainable investing preference, in comparison to conventional investment decisions.

Hp_1: Variables traditionally associated with investment decisions (i.e., financial literacy, financial self-efficacy, risk attitudes, future orientation, and ambiguity tolerance) are associated with both conventional and socially responsible investing.

Hp_2: Variables traditionally associated with investment decisions (i.e., financial literacy, financial self-efficacy, risk attitudes, future orientation, and ambiguity tolerance) have less explanatory power in predicting socially responsible investing than conventional investment intentions.

3. Methods

3.1 Sample

For research purposes, anonymized data were obtained from an online survey filled in March 2022 by a sample of 938 Italian consumers. Respondents were recruited through Prolific and received a small incentive for study participation. The questionnaire was distributed via the Qualtrics online survey platform. Written informed consent was obtained from all participants before the questionnaire was administered.

The sample consisted of 40.2% women and 59.8% men, with ages ranging from 18 to 74 years (M = 48.86, SD = 14.09). In terms of educational level, most respondents had a high school diploma (62.6%), 9.9% had a middle school diploma, and 27.5% had attended university. Considering geographical area, 53.7% of participants lived in the north of the country (precisely, 23% in the north-west and 20.7% in the north-east), 23.2% in the central part of Italy, while the remaining 33.1% came from southern regions.

In addition to socio-demographic information, respondents were asked if they were currently investing in financial markets: 43% were financial investors, while 57% were not investing in financial markets.

3.2 Measure

3.2.1 Financial literacy

Financial literacy was measured using 4 questions. The “Big 3” questions developed by Lusardi and Mitchell (2011) were employed, which assess individuals' knowledge of interest rates, inflation, and risk diversification. Furthermore, an additional item was developed to test the understanding of the risk-return trade-off: “There is a direct link between risk and the return on a financial asset, so an investment with a high expected return is probably very risky”. Participants were required to select the correct answer from three or four alternatives. The index of financial literacy was obtained by adding the number of correct answers. The total score ranged between 0 (no correct answers) and 4 (all answers correct).

3.2.2 Financial self-efficacy

To measure individuals' perceptions of and confidence in their own financial skills, competencies, and knowledge, a single item was developed ad hoc: "Overall, how much do you feel confident in your skills and competences in financial management?". Participants rated their perceived confidence on a Likert scale ranging from 1 (not confident at all) to 7 (very confident).

3.2.3 Financial risk attitude

To assess risk attitude (i.e., the general construct encompassing risk tolerance and risk aversion, which is the opposite of risk tolerance) in financial and investment domains, a six-item scale from Kapteyn and Teppa (2011) was used. Respondents rated their agreement on a Likert scale ranging from 1 (completely disagree) to 7 (completely agree). The measure comprises two factors, each assessed with three items. The first factor represents financial risk aversion ($\omega = .671$), while the second assesses financial risk tolerance ($\omega = .818$). Higher scores indicate higher levels of risk aversion and risk tolerance, respectively.

3.2.4 Future orientation

To assess consumers' future orientation, the Italian version of the Consideration of Future Consequences-14 Scale (CFC-14; Nigro et al., 2016) was used. Only the subscale measuring concerns for future consequences (CFC-Future; $\omega = .736$) was administered in the present study. The subscale is composed of 7 items (e.g., "I am willing to sacrifice my immediate happiness or wellbeing in order to achieve future outcomes"). Respondents rated their answers on a Likert scale ranging from 1 (extremely uncharacteristic) to 7 (extremely characteristic).

3.2.5 Ambiguity tolerance

Attitude towards ambiguity was assessed using the Italian version of the Multidimensional Attitude towards Ambiguity Scale (MAAS; Lauriola et al., 2016). This tool measures the psychological personality construct related to individual reactions to perceived ambiguous stimuli in various contexts and situations. The scale is composed of 30 items, distributed on three subscales. In the present study, only the Discomfort with Ambiguity subscale ($\omega = .828$) was used, which refers to the affective component of the construct and is measured with 10 items (e.g., "It intensely disturbs me when I am uncertain of how my actions will affect others"). Respondents had to express their agreement on a Likert scale ranging from 1 (I strongly disagree) to 7 (I strongly agree).

3.2.6 Willingness to invest

The path analytic model estimated in the present study involves two dependent variables. Specifically, the intention to invest both in conventional financial assets and in socially responsible products was measured. The two dependent variables were assessed through a single item each. As for conventional willingness to invest, respondents were asked to answer to a statement created ad hoc: "How likely are you to invest your money in the next 6 months?". Answers ranged on a seven-point Likert scale (1 = I will not invest at all; 7 = I will definitely invest).

After briefly explaining what sustainable investments entail, consumers' intentions regarding Socially Responsible Investing (SRI) were measured with a second statement ("To what extent would you consider investing in sustainable investment products?"). Answers ranged on a seven-point Likert scale (1 = I will not invest at all; 7 = I will definitely invest).

3.2.7 Control variables

Control variables were included to account for potential confounding factors that could influence the main outcomes. In other words, control variables were selected to ensure a more accurate analysis of the relationships under investigation. Specifically, sociodemographic characteristics, namely gender, age, and education level were included as they might play a role in investment behavior. Additionally, we included investment status as a control variable to distinguish those investing in financial market from non-investors. To assess investment status, respondents were asked to report if they were currently investing in financial markets. The variable was thus measured through a dummy variable, where 0 = non-investor and 1 = financial investor.

4. Data analysis

To test whether financial decision-making determinants predict the intention to invest in both conventional and sustainable financial assets, a path analytic regression model was estimated (aim 1). Subsequently, equality constraints were added to the model to measure paths invariance across the two kinds of investment (i.e., investment intentions in conventional vs. sustainable financial products). This enabled us to verify whether variables included in the model had less explanatory power in predicting the willingness to invest in SRI compared to conventional assets. (aim 2). Figure 1 represents the theoretical model.

4.1 Confirmatory factor analysis

First, Confirmatory Factor Analyses (CFA) were estimated to verify the theoretical model and assess the factorial structure of the scales considered in the present study. Various statistics were considered to evaluate the goodness of fit of the model(s): the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Standardized Root Mean Square Residual (SRMR) were calculated. Scores of RMSEA and SRMR lower than .08 are considered acceptable, while a CFI higher than .90 indicates a good fit. (Marsch et al., 2004). The confidence intervals (90%) of RMSEA (Little, 2013) and χ^2 significance tests were checked as well, though the latter is strongly influenced by sample size (Bentler & Bonett, 1980). Factor scores were then saved, to obtain more reliable estimates to use in the subsequent analyses (Meyer & Morin, 2016).

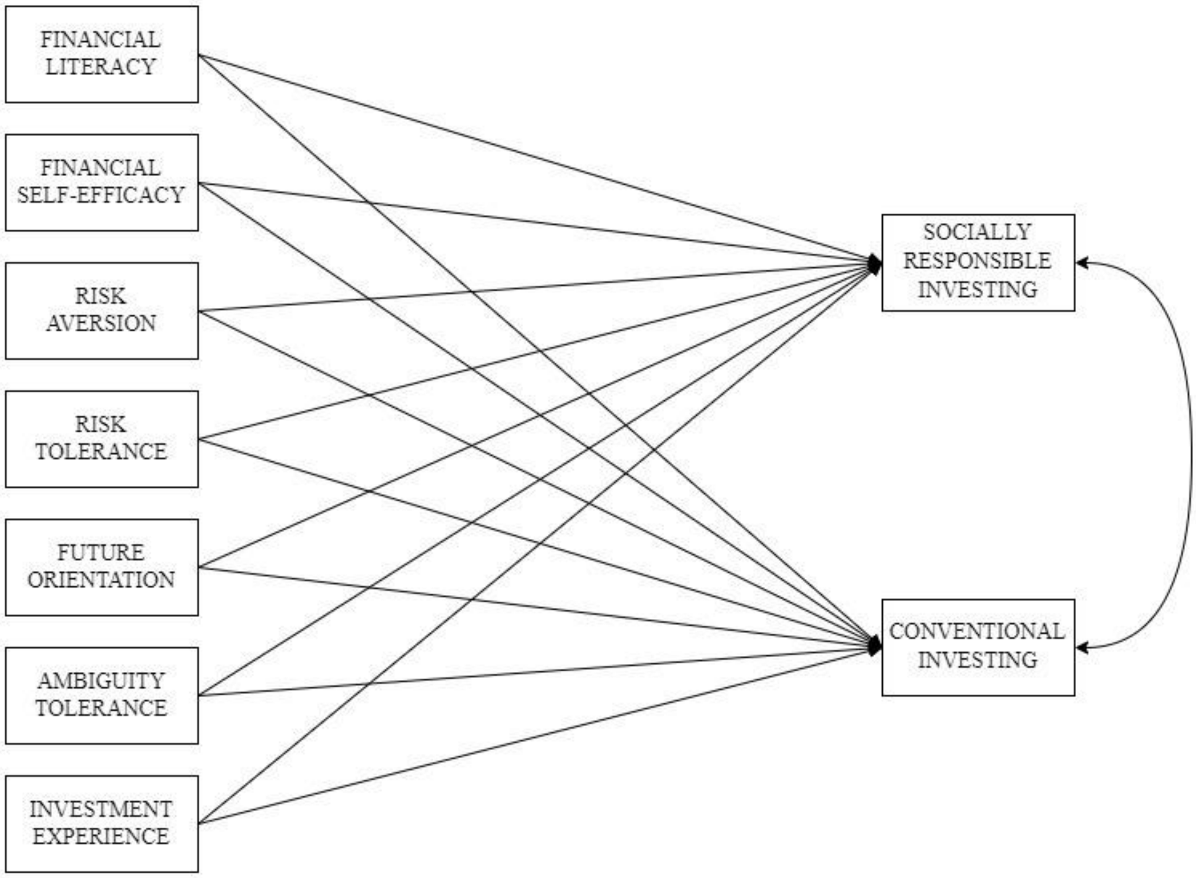

Figure 1.

The estimated structural equation model. Correlations between predictors are not represented.

4.2 Estimating the path analytic model

After checking the psychometric scales, a path analytic regression model was then performed to test the role of financial literacy, financial self-efficacy, financial risk attitudes (i.e., risk tolerance and risk aversion), future orientation, and attitudes toward ambiguity on the willingness to invest both in conventional and sustainable financial assets. Socio-demographic variables (i.e., gender, age, and education) were also considered as control variables. To compare the paths for each determinant on the two outcomes, conventional and sustainable investing intentions were included simultaneously in the regression model, which can be represented as follows:

$Y_{1,i} = \beta_{1,0} + \beta_{1,1}$Gender + $\beta_{1,2}$Age + $\beta_{1,3}$Education + $\beta_{1,4}$Investment status + $\beta_{1,5}$Financial Literacy + $\beta_{1,6}$Financial Self-efficacy + $\beta_{1,7}$Risk Aversion + $\beta_{1,8}$Risk Tolerance + $\beta_{1,9}$Future Orientation + $\beta_{1,10}$Ambiguity Tolerance + ϵ_1

$Y_{2,i} = \beta_{2,0} + \beta_{2,1}$Gender + $\beta_{2,2}$Age + $\beta_{2,3}$Education + $\beta_{2,4}$Investment status + $\beta_{2,5}$ Financial Literacy + $\beta_{2,6}$Financial Self-efficacy + $\beta_{2,7}$Risk Aversion + $\beta_{2,8}$Risk Tolerance + $\beta_{2,9}$Future Orientation + $\beta_{2,10}$Ambiguity Tolerance + ϵ_2

$Cov(X_j,X_k)$

$Cov(\epsilon_1,\epsilon_2) = \rho$

Where Y_1 refers to the score of conventional investing intentions, while Y_2 stands for sustainable investing intentions and i indicates the respondent. $\beta_{1,0}$ and $\beta_{2,0}$ represent the intercepts for the conventional and sustainable investing equations, respectively. Structural equation models also estimate covariances between predictors (i.e., $Cov(X_j, X_k)$, where X_j and X_k represent all the potential couples of predictors) to account for potential interrelations among them, therefore providing more reliable estimates of the effects of predictors on the outcomes. Furthermore, a correlation between the residuals of the two equations (i.e., $Cov(\epsilon_1,\epsilon_2) = \rho$) was imposed. This approach is standard in Structural Equation Modeling to also account for the relationship between the two dependent variables included in the model.

Analysis was performed in Mplus 8.7. Model goodness of fit was evaluated considering the following indexes: χ^2 value, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). Scores of RMSEA and SRMR below the cutoff of .08 are considered acceptable, while a CFI greater than .90 indicates a good fit (Marsch et al., 2004). The χ^2 value was also considered, although it is heavily influenced by sample size. Specifically, a non-significant χ^2 value indicates a better fit for the model. However, this test tends to show significant differences with larger sample sizes.

4.3 Testing invariance across regression paths of the model

Once the path analytic model was estimated, equality constraints were added to evaluate whether the regression paths linking the predictors (i.e., financial literacy, financial self-efficacy, risk tolerance, risk aversion, future orientation, ambiguity tolerance, investment status, and socio-demographic variables) to the outcomes (i.e., willingness to invest in conventional assets and intentions toward SRI) were invariant for the two kinds of investment. The model constraining imposed the paths to be equivalent across the two outcomes (e.g., the impact that financial literacy has on the "willingness to invest in conventional assets" is assumed to be equivalent to the impact that financial literacy has on the "willingness to invest in sustainable financial products"). The constrained path analysis is expressed as follows. First, each coefficient of the function was constrained to be equal for the two outcomes:

$\beta_{1,1}\text{Gender} = \beta_{2,1}\text{Gender} = \gamma_1\text{Gender}$

$\beta_{1,2}\text{Age} = \beta_{2,2}\text{Age} = \gamma_2\text{Age}$

$\ldots\ \beta_{1,k} = \beta_{2,k} = \gamma_k$

The fully constrained regression model then becomes:

$Y_{i,1} = \beta_{1,0} + \gamma_1$Gender + γ_2Age + γ_3Education + γ_4Investment status + γ_5Financial Literacy + γ_6Financial Self-efficacy + γ_7Risk Aversion + γ_8Risk Tolerance + γ_9Future Orientation + γ_{10}Ambiguity Tolerance $+\epsilon_1$

$Y_{i,2} = \beta_{2,0} + \gamma_1$Gender + γ_2Age + γ_3Education + γ_4Investment status + γ_5Financial Literacy + γ_6Financial Self-efficacy + γ_7Risk Aversion + γ_8Risk Tolerance + γ_9Future Orientation + γ_{10}Ambiguity Tolerance $+\epsilon_2$

$\mathrm{Cov}(X_j,X_k)$

$\mathrm{Cov}(\epsilon_1,\epsilon_2) = \rho$

Where γ_k represent the regression paths constrained to be equal across the two outcomes (i.e., $\beta_{1,k} = \beta_{2,k} = \gamma_k$). Basically, in the constrained model, each predictor was initially assumed to have the same effect on both outcomes (i.e., $\beta_{1,k} = \beta_{2,k}$). After the effect of a variable is constrained across the two outcomes (i.e., willingness to invest in both conventional and sustainable investment products), it is represented by a single coefficient (i.e., γ_k). The resulting regression equations thus included γ_k terms to represent these equality constraints.

Subsequently, the model fit was assessed by comparing the constrained model to the baseline (i.e., the model without equality constraints on the paths) model. Differences in the CFI index between the baseline model (i.e., the model without equality constraints on the paths) and the constrained model were measured to test whether the goodness of fit consistently decreased. Considering sample size ($N > 400$), a decrease in the CFI index equal or higher than .01 suggests a significant decline of the model fit (Chen, 2007). Whenever CFI index differences indicate a meaningful worsening of fit, the constrained model should be modified by removing equality constraints for the non-invariant paths (i.e., $\beta_{1,k} \neq \beta_{2,k}$) in

Table 1.

Descriptive statistics and correlations for continuous variables included in the path analytic model.

Variable	M	SD	1	2	3	4	5	6
1. Financial Literacy	2.55	1.29	1					
2. Financial Self-Efficacy	4.22	1.38	.100**	1				
3. Financial Risk Aversion	5.09	1.09	.032	-0.077*	1			
4. Financial Risk Tolerance	3.53	1.49	-0.121***	.200***	-0.456***	1		
5. Future Orientation	4.84	1.01	.046	.174***	.263***	.191***	1	
6. Ambiguity Tolerance	4.27	.78	-0.135**	.004	.131***	.304***	.440***	1

Note. M = Mean; SD = Standard Deviation; * $p < .05$; ** $p < .01$; *** $p < .001$.

order to improve the model fit. Equality constraints were progressively removed until the difference in CFI between the constrained and baseline models was less than .01. Modification indices, reported in the Mplus output, were considered to evaluate which path(s) were not equivalent and, therefore, to be released (Dimitrov, 2010). The partially constrained regression model finally becomes:

$Y_{i,1} = \beta_{1,0} + \gamma_1$Gender + γ_2Age + γ_3Education + $\beta_{1,4}$Investment status + γ_5Financial Literacy + γ_6Financial Self-efficacy + $\beta_{1,7}$Risk Aversion + $\beta_{1,8}$Risk Tolerance + γ_9Future Orientation + $\beta_{1,10}$Ambiguity Tolerance +ϵ_1

$Y_{i,2} = \beta_{2,0} + \gamma_1$Gender + γ_2Age + γ_3Education + $\beta_{2,4}$Investment status + γ_5Financial Literacy + γ_6Financial Self-efficacy + $\beta_{2,7}$Risk Aversion + $\beta_{2,8}$Risk Tolerance + γ_9Future Orientation + $\beta_{2,10}$Ambiguity Tolerance +ϵ_2

$\mathrm{Cov}(X_j,X_k)$

$\mathrm{Cov}(\epsilon_1,\epsilon_2) = \rho$

Where γ_k represent the regression paths that are equal across the two outcomes (i.e., $\beta_{1,k} = \beta_{2,k} = \gamma_k$). Variables with non-invariant paths (i.e., $\beta_{1,k} \neq \beta_{2,k}$) are instead represented as $\beta_{1,k}$ and $\beta_{2,k}$, since they were unconstrained and freely estimated for the two outcomes. In other words, if the effect of a variable on both outcomes is equivalent, the path is constrained and represented as γ_k. If the effect of a variable differs across the outcomes, the paths are estimated freely and denoted as $\beta_{1,k}$ and $\beta_{2,k}$.

5. Results

Table 1 represents descriptive statistics for each measure considered in the analyses. Data normality for continuous variables was checked according to Muthén and Kaplan (1985)'s cut-off (± 2). Skewness ranged from -0.462 to .022, while kurtosis values were between -0.915 and .464. Multicollinearity was also controlled by estimating the Variance inflation factor (VIF). VIF values ranged from 1.112 to 1.702, thus below the suggested cut-off of 5 (Kim, 2019). Table 2 reports goodness-of-fit indices for the CFAs performed on the psychometric scales, while items factor loadings and composite reliability (i.e., McDonald's ω) scores are represented in Table 3.

Table 2.

Fit indices of the Confirmatory Factor Analysis (CFA)

Variable	χ^2	*df*	p	RMSEA (90% CI)	CFI	SRMR
Financial risk attitudes	64.458	8	< .001	.087 (.068, .107)	.945	.042
Future orientation	54.626	14	< .001	.056 (.041, .072)	.937	.039
Ambiguity tolerance	43.444	14	< .001	.047 (.032, .064)	.975	.026

Note. χ^2 = chi-square; *df* = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residuals.

5.1 Estimating the path analytic model (aim 1)

The estimated model was saturated, which means that the fit indices could not be used to evaluate the goodness of the model since it has a perfect fit. Table 4 summarizes results obtained with the path analysis. Specifically, considering the intention to invest in conventional financial assets, risk tolerance resulted the strongest predictor ($\beta = .300$; $p < .001$), while risk aversion was negatively associated with investment intentions ($\beta = -.081$; $p = .028$). Findings showed that financial self-efficacy ($\beta = .148$; $p < .001$), future orientation (β

= .084; p = .016) and investment status (β = .240; p < .001) were significantly related to conventional investment intention. The model resulted quite similar in explaining consumers' willingness to invest in SRI, as financial self-efficacy (β = .124; p = .001), risk tolerance (β = .269; p < .001), future orientation (β = .132; p = .001), and investment status (β = .173; p < .001) played a significant role as well in sustainable investment decisions.

Surprisingly, financial literacy and ambiguity tolerance resulted non-significant in both cases. Hp_1 is thus confirmed, since the willingness to invest in SRI is accounted for by classical determinants of investment decisions.

5.2 Testing invariance across regression paths of the model (aim 2)

Once the regression paths in the model were constrained to be invariant across the two outcomes, model fit indices vertiginously decreased, suggesting that one or more of the imposed constraints was not plausible. Consequently, equality constraints were progressively removed from non-invariant paths until the difference in fit between the baseline and constrained models was no longer significant. (i.e., ΔCFI < .010). Table 5 reports the parameters that were released (i.e., risk aversion, risk tolerance, investment status, and ambiguity tolerance) and model goodness of fit. The final constrained model reported good fit indices (RMSEA < .08; CFI > .90; SRMR < .08).

Findings, reported in Table 6, showed that financial self-efficacy and future orientation were the only variables invariant in explaining conventional and sustainable investment intentions. Otherwise, financial risk attitudes (i.e., risk tolerance and risk aversion), ambiguity tolerance and investment status played different roles in predicting investment decisions. It is worthy of attention that non-invariant predictors, as expected, resulted to have less explanatory power towards the intention to invest in SRI. In particular, whereas risk aversion is negatively associated with conventional willingness to invest (β = -0.090; p = .036), it is incapable of predicting socially responsible investing (p =.060). A

Table 3.

Descriptive statistics, standardized factor loadings, and reliability scores for the psychometric scales

Variable	M (SD)	Loading	CR
Financial risk attitudes			.671
Factor 1 (Aversion)			
1. Penso che sia più importante fare investimenti prudenti con ritorni garantiti, invece che assumermi dei rischi per avere la possibilità di ottenere rendimenti più alti	5.28 (1.29)	.740***	
2. Non considererei mai investimenti di tipo azionario perché li reputo troppo rischiosi	4.54 (1.61)	.514***	
3. Voglio essere certo che i miei investimenti siano sicuri	5.44 (1.28)	.695***	
Factor 2 (Tolerance)			.818
1. Se penso che un investimento possa essere redditizio, sono disposto/a chiedere un prestito per fare questo investimento	3.70 (1.69)	.721***	
2. Sono sempre più convinto che dovrei assumermi maggiori rischi finanziari per migliorare la mia situazione finanziaria	3.58 (1.68)	.803***	
3. Sono disposto ad assumermi il rischio di perdere del denaro a fronte della possibilità di guadagnare dei soldi	3.31 (1.84)	.801***	
Future orientation			.736
1. Penso a come le cose potrebbero essere in futuro, e tento di influenzarle con il mio comportamento quotidiano	4.91 (1.17)	.589***	
2. Spesso mi impegno in un particolare comportamento per raggiungere risultati che potrebbero non realizzarsi per molti anni	4.63 (1.25)	.487***	
3. Sono disposto a sacrificare la felicità o il benessere immediato per raggiungere risultati futuri	4.19 (1.46)	.445***	
4. Penso sia importante prendere sul serio gli avvertimenti sulle conseguenze negative di un comportamento, anche se tali conseguenze non si verificheranno per anni e anni	5.14 (1.18)	.541***	

5. Penso sia più importante adottare un comportamento che abbia conseguenze rilevanti a lungo termine, piuttosto che un comportamento con conseguenze immediate ma meno importanti	5.04 (1.19)	.590***	
6. Quando prendo una decisione, penso a quali effetti potrebbe avere su di me in futuro	5.28 (1.22)	.578***	
6. Il mio comportamento è generalmente influenzato dalle conseguenze future	4.65 (1.25)	.538***	
Ambiguity tolerance			.828
1. Mi dà estremamente fastidio quando non sono sicuro/a di come i miei comportamenti influiscono sugli altri	4.38 (1.32)	.621***	
2. Mi sento un po' a disagio con la gente fino a quando non riesco in qualche modo a comprendere il loro comportamento	4.41 (1.41)	.735***	
3. Non mi sento a mio agio con la gente fino a quando non scopro qualcosa su di loro	4.13 (1.41)	.661***	
4. Divento molto ansioso/a quando sono in una situazione sociale che mi coinvolge ma di cui ho poco controllo	4.52 (1.42)	.644***	
5. Mi dà fastidio non sapere come le altre persone reagiscono nei miei confronti	4.17 (1.45)	.663***	
6. Se non è chiaro quale siano le mie responsabilità nel lavoro, divento molto ansioso/a	4.42 (1.42)	.594***	
7. Se non afferro immediatamente l'umorismo di una barzelletta, mi sento a disagio fino a quando non riesco a comprenderlo	3.83 (1.62)	.564***	

Note. M = Mean; SD = Standard Deviation; Loading = Standardized factor loading; CR = Composite Reliability; *** $p < .001$.

similar trend occurs for risk tolerance, which had a greater value for conventional investment intentions ($\beta = .305$; $p < .001$), rather than for SRI ($\beta = .266$; $p < .001$). Ambiguity tolerance also had a different predictive power for the two outcomes. While it was positively associated with conventional willingness to invest, it was negatively related to the intention toward sustainable investments. However, this trend is less relevant since regression paths turned out to be non-significant for both the outcomes. As for investment status, it emerged to have a greater role in explaining the willingness to invest conventionally ($\beta = .241$; $p < .001$), compared to sustainable investing intentions ($\beta = .172$; $p < .001$). This means that investors are more willing to invest in conventional financial assets than sustainable ones.

Overall, the constrained model was less explanatory in describing the intention to invest in sustainable financial assets. In particular, the model explained a higher portion of variance for the willingness to invest in conventional assets ($R^2 = .306$) rather than sustainable investment intentions ($R^2 = .189$). The results obtained from the path analytic model, as well as differences in the variance explained (R^2), supported Hp_2.

6. Discussion

The literature on socially responsible investing in Europe primarily originates from northern countries, such as Germany, Holland, and Sweden. To the best of our knowledge, no studies have yet explored consumers' sustainable investment decisions in the Italian context. This study aimed to examine whether variables commonly associated with investment decisions also influence the intention to invest in SRI. Precisely, cross-sectional data were used to perform a path analytic regression model. The impact of financial literacy, financial self-efficacy, risk attitude (i.e., risk tolerance and risk aversion), future orientation, and ambiguity tolerance on investment intentions for both conventional and sustainable assets was assessed. Furthermore, for research purposes, we investigated whether these variables

Table 4.

Regression coefficients of each predictor in the path analytic model where coefficients were free to vary across the two outcomes.

Variable	Conventional investing			Socially responsible investing		
	β	SE	p	β	SE	p
Gender[1]	.032	.030	.287	-0.022	.032	.498
Age	-0.051	.031	.093	-0.046	.033	.159
Education	.005	.030	.867	.048	.033	.142
Financial Literacy	.009	.028	.758	.038	.031	.233
Financial Self-Efficacy	.148	.032	<.001	.124	.037	.001
Risk Aversion	-0.081	.037	.028	.068	.041	.095
Risk Tolerance	.300	.039	<.001	.269	.043	<.001
Future Orientation	.084	.035	.016	.132	.040	.001
Ambiguity Tolerance	.061	.037	.095	-0.030	.041	.466
Investment Experience[2]	.240	.029	<.001	.173	.031	<.001

Note. [1] 0 = female; 1 = male; [2] 0 = non-investor 1 = investor; Standardized values are reported.

Table 5. Fit indices of the partial constrained model

	χ^2	*df*	p	RMSEA (90% CI)	CFI	Δ_{CFI}	SRMR
Free model	.000	0	<.001	.000 (.000 .000)	1.000	-	.000
Constrained model	83.609	10	<.001	.089 (.072 .107)	.882	.118	.065
- Freeing Risk Aversion	38.870	9	<.001	.059 (.041 .079)	.952	.048	.042
- Freeing Risk Tolerance	24.038	8	.002	.046 (.026 .068)	.974	.026	.024
- Freeing Investment Experience	12.998	7	.072	.030 (.000 .056)	.990	.010	.015
- Freeing Ambiguity Tolerance	8.183	6	.225	.020 (.000 .050)	.996	.004	.013

Note. χ^2 = chi-square; *df* = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residuals.

Table 6.

Regression coefficients for the path analysis, in which coefficients were constrained to be equivalent across the two outcomes

Variable	Conventional investing			Socially responsible investing		
	β	SE	p	β	SE	p
Gender[1]	.002	.024	.923	.003	.029	.923
Age	-0.044	.024	.071	-0.053	.029	.071
Education	.025	.024	.287	.031	.029	.288
Financial Literacy	.022	.023	.347	.026	.028	.348
Financial Self-Efficacy	.121	.027	<.001	.146	.033	<.001
Risk Aversion	**-0.090**	.036	.013	**.075**	.034	.060
Risk Tolerance	**.305**	.038	<.001	**.266**	.043	<.001
Future Orientation	.099	.028	<.001	.119	.040	.001
Ambiguity Tolerance	**.053**	.036	.138	**-0.023**	.040	.560
Investment Experience[2]	**.241**	.029	<.001	**.172**	.031	<.001

Note. [1] 0 = female; 1 = male; [2] 0 = non-investor 1 = investor; Standardized values are reported; Bold coefficients are significantly different for the two outcomes had the same explanatory power in determining consumers' willingness to invest in SRI, compared to conventional investing intentions.

Findings revealed that variables commonly associated with investment decision-making also predict socially responsible investing. To be precise, financial self-efficacy, risk tolerance, and future orientation were significantly associated with the willingness to invest in SRI. Among control variables, only investment status played however a significant role in explaining sustainable investing intentions. Surprisingly, financial literacy and ambiguity tolerance failed in explaining consumers' investment intentions toward SRI. Consistent with prior research (e.g., Montford & Goldsmith, 2016), our results suggest that investment decision-making could be affected more by perceived financial skills and knowledge rather than actual competences. In other words, financial self-efficacy may hold greater significance than objective financial literacy. Concerning the role of ambiguity tolerance, it seems that it might play only a marginal role in shaping investment decisions, as its influence might be overshadowed by other variables included in the model. Finally, socio-demographic variables (i.e., gender, age, and education) were non-significant. This finding supports the idea that socio-demographics alone are inadequate for differentiating between conventional investors and those who choose SRI.

Variables explaining sustainable investing intentions were associated with the willingness to invest in conventional assets as well. Anyway, we found two main differences in how classical determinants of investment decision-making influence conventional and sustainable investment intentions. First, risk attitude (i.e., risk aversion and risk tolerance) had differing effects. Indeed, risk tolerance had a greater explanatory power for conventional investment intentions, while risk aversion was significant only for conventional assets. These findings are in accordance with previous studies (e.g., Delsen & Lehr, 2019), which suggests that risk appetite plays a lesser role in shaping consumers' willingness to invest ethically.

Similarly, investment status plays a lesser role in explaining the willingness to invest in SRI compared to its influence on conventional investment intentions. In other words, those investing in financial markets were more likely to prefer conventional investing over SRI.

Despite the contribution to socially responsible investing literature, the present study is not lacking limitations. First, only survey data were used. Considering that self-report measures were administered, answers might be somehow biased by social desirability. Moreover, cross-sectional data do not allow us to draw clear inferences. Furthermore, considering that the sample is composed only by Italian consumers and the exploratory nature of the study, conclusions should be taken cautiously. Secondly, our study focused only on classical determinants of investment decisions, without considering also ethical values, attitudes, and ecological concerns that could influence the decision to invest in SRI. A third limitation of our study is the absence of income as a control variable. Given that income can significantly influence investment decisions, its omission may affect the robustness of our findings. Future research should consider including income as a control variable to enhance the comprehensiveness of the role of income within SRI.

Overall, it seems that variables usually related to investment decisions are not enough to determine why people invest in SRI. These findings make us conclude that other factors might come into play in shaping sustainable investing decision making, since SRI might involve different decision criteria in comparison to conventional investment products. Pro-environmental values, attitudes, barriers, and other personal characteristics that go beyond classical investment decision processes could indeed play a significant role in the decision process.

CHAPTER 2

MEASURING BIOSPHERIC VALUES: ITALIAN ADAPTATION OF THE GREEN SCALE

The present chapter reports the validation process of the Italian adaptation of the GREEN scale (Haws et al., 2014), a psychometric instrument measuring personal values towards environmental sustainability. Specifically, the validation process was carried out following the *contemporary view of validity* guidelines. Hence, different kinds of validity evidence were collected to evaluate the construct validity of the instrument. This adaptation relates to the broader scope of the doctoral project, as the GREEN scale will be employed as a measure in the study presented in the following chapter.

The chapter is structured as follows. Section 1 provides a detailed theoretical background of biospheric values and the psychological scales to measure this construct. Then, the theoretical framework of the study is presented in Section 2. The methodology of the study is outlined in Section 3. Finally, results are summarized in Section 4 and discussed in Section 5.

1. Theoretical background

Climate change is one of the biggest threats that mankind is called to deal with from now to the next few decades, requiring people to shift their habits by pursuing more environmentally-friendly behaviors and consumption. In the last decade, the psychological literature on sustainability has grown considerably. Specifically, a relevant research field concerns the investigation of psychological characteristics associated with pro-environmental behaviors. Various researchers highlighted the relevant role played by personal values in adopting environmentally-friendly behaviors and sustainable consumption habits. According to Schwartz (1992), values function as guiding principles in individuals' lives, influencing their actions. Furthermore, values are abstract and general constructs that apply to a wide range of contexts, because they transcend specific domains and situations. Concerning environmental domains, scholars generally talk about biospheric (or environmental) values, namely self-transcendent values reflecting the concern for caring for and preserving the natural environment (De Groot & Steg, 2010).

Previous studies reported a strong association between them and environmental protection behaviors (De Groot & Steg, 2009; Katz-Gerro et al., 2017; Ruepert et al., 2017; Wang et al., 2021). For instance, Bouman et al. (2020) showed in a cross-country study that biospheric values are related to both worry about climate change and energy-saving behaviors. Likewise, consumers with stronger biospheric values are more prone to purchasing organic products (van Doorn & Verhoef, 2015). Values can also influence individuals' attitudes. Indeed, a strong impact of values on environmental attitudes was reported by various studies (e.g., Schultz & Zelezny, 1999; Steg et al., 2014). For instance, in a cross-cultural comparison, Schultz et al. (2005) found a significant association between values and environmental concern, that is, a general attitude referring to a personal evaluation of environmental issues (De Groot & Thøgersen, 2018). Biospheric values are also related to a willingness to sacrifice personal interests for the environment (Rahman & Reynolds, 2016) and to think about the environmental consequences of one's actions (Perlaviciute & Steg, 2015).

1.1 Psychometric instruments measuring biospheric values

Despite the topic relevance, only a few psychometric scales assess values in environmental domains. The most widely used instruments were created relying on Schwartz's value theory. Specifically, according to this theoretical framework (Schwartz, 1992, 1994), values can be distinguished between self-enhancement and self-transcendence. While the former are more focused on the concerns for personal interests, the latter refer to stronger interests for collectivity. These two types of values are differently associated with pro-environmental behaviors. Indeed, while self-transcendence values positively affect environmentally-friendly behaviors, self-enhancement values are typically negatively related to them (Bouman et al., 2018).

Steg et al. (2014) proposed the Environmental-SVS (E-SVS), which has been adapted from the Schwartz Value Survey (SVS; Schwartz, 1994). This tool consists of 16 items measuring four values. Indeed, as suggested by the authors, four specific values are relevant in predicting pro-environmental behaviors. Among self-transcendent values, there are biospheric and altruistic (i.e., concerns for the welfare and fair treatment of other individuals) values. Among self-enhancement values, there are egoistic and hedonic values. The former refers to the maximization of personal outcomes, while hedonic values focus on the search for pleasure and positive feelings (De Groot & Thøgersen, 2018). The SVS received various critiques over time, and the same concerns could be applied to the E-SVS as well (Bouman et al., 2018). Specifically, the items are developed in a way that might enhance the self-presentation bias in the answers. Furthermore, respondents may find it difficult to answer the items of the scale, thus affecting the validity and reliability of the measure itself. To overcome the limits of the SVS, Schwartz et al. (2012) proposed the Portrait Values Questionnaire (PVQ), which is currently considered the gold standard for values assessment. Among the 10 different motivational behaviors, the PVQ measures universalism, in which altruistic and biospheric values are embedded and assessed with three items each. Recently, Bouman et al. (2018) adapted the PVQ to specifically measure values in environmental domains by developing the Environmental Portrait Values Questionnaire (E-PVQ). This instrument assesses four types of values: biospheric, altruistic, hedonic, and egoistic. To date, neither the E-SVS nor the E-PVQ have been adapted yet to the Italian context.

However, studies report that, among these values, the biospheric ones are the strongest predictors of pro-environmental behaviors (e.g., Katz-Gerro et al., 2017), thus suggesting the possibility to specifically focus on them. Furthermore, in some situations, altruistic and biospheric values could be conflicting, for instance when primed at the same time (De Groot & Thøgersen, 2018; van Doorn & Verhoef, 2015). As suggested by De Groot and Steg (2007), though related, biospheric and altruistic are distinct types of self-transcendence values and, in some contexts, they may contribute uniquely to explaining human behavior. Therefore, it may be useful to consider biospheric and altruistic values independently, given that they have a different focus.

A specific measure for biospheric values is the GREEN scale (Haws et al., 2014), a brief tool reflecting the extent to which individuals pay attention to the conservation of natural resources in their daily behavior. The measure is composed of six items, developed on a 7-point Likert scale, and it was originally proposed in English. This scale has been used in various domains. For instance, it positively predicted attitudes toward environmentally-friendly products (Pegan et al., 2023), like cultured meat (Dupont et al., 2022) and bio-based apparel (Stahl et al., 2021). Likewise, the GREEN scale was found to predict sustainable consumption behaviors (e.g., Dikici et al., 2022; Paço et al., 2019).

This instrument has been used in various countries, such as the United States (Bailey et al., 2018), Germany (Klein et al., 2020; Macht et al., 2023), the United Kingdom (Paço et al., 2019; Ribeiro et al., 2023), Austria (Essiz & Mandrik, 2021), Poland (Bartoszczuk et al., 2022), and Turkey (Dikici et al., 2022). The measure was adopted for research purposes within the Italian context as well (e.g., Bonera et al., 2020; Mazzocchi et al., 2021; Risitano et al., 2023), though without testing its psychometric properties. This data further suggests the usefulness of an Italian adaptation of the GREEN scale. Indeed, to date, there is no validation of the measure, despite its good psychometric properties and its brevity allow researchers to use it in different settings and easily integrate it in longer surveys. An Italian adaptation of the scale could be useful to both enhance our theoretical understanding of how values shape human behavior in environmental domains (e.g., cross-cultural comparisons) and develop interventions to promote pro-environmental behaviors. Likewise, it could also be useful in marketing and sustainable consumption research.

2. Theoretical framework

The conception of validity has changed multiple times during the last century and the different conceptions in vogue nowadays share some common assumptions that are identified by the expression "contemporary view of validity" (Peeters & Harpe, 2020). Three main differences distinguish the traditional view(s) of validity from the contemporary view(s) of validity (Sorgente & Zumbo, in press; Zumbo, 2005, 2006). First, validity is no longer a property of a test. According to the traditional view of validity, once the test developer has demonstrated that a test measures what it claims to measure, the test is valid per se, and it can be adopted in future studies with the inherent assurance that the instrument is adequate to assess the construct of interest. However, according to the contemporary view of validity, "trying to define validity as a property of tests quickly leads to absurdities since the validity of a test can vary from population to population" (Wiliam, 2014, p. 29). In other words, a researcher has to consider whether there is sufficient evidence in the research literature to "support the appropriateness, meaningfulness, and usefulness of the specific inferences made from scores about individuals from a given sample and in a given context" (Zumbo, 2006, p. 48), and, if not, that evidence needs to be provided. This implies that validity is contextualized; we cannot validate a test per se, because the validity of a test may change from one context to another (e.g., different countries, samples, and age groups).

This contextualized validity implies a second difference between the traditional and contemporary views of validity. Whereas according to the traditional view, test developers are the only ones who must evaluate whether an instrument is valid or not, the contemporary view also calls for test users (i.e., researchers, clinicians, and practitioners adopting the psychometric instrument), together with test developers, to prove the validity of the scores obtained from a test in a specific sample or context.

Finally, the contemporary view proposed a unified conception of validity. According to the traditional view of validity, different kinds of validity exist (e.g., content, predictive, concurrent, and construct validity), and each of these "validities" is treated as sufficient evidence on its own. The contemporary view of validity (Messick, 1989, 1995) suggests instead that test developers and users should specifically evaluate the *construct validity* of their scores. Because "construct validity cannot generally be expressed in the form of a single simple coefficient" (Cronbach & Meehl, 1955, p. 201), the validation process requires collecting multiple sources of validity evidence to prove that the test scores measure the construct they prompt to measure (i.e., construct validity; Peeters & Harpe, 2020). In particular, one may formulate a list of hypotheses to empirically demonstrate the theory (e.g., the construct should have X dimensions, be associated with variable Y, predict variable Z, etc.). Testing these hypotheses and finding evidence to support them means collecting evidence of construct validity. This description focuses on different kinds of evidence (e.g., convergent evidence) rather than diverse kinds of validity (e.g., convergent validity).

Hubley and Zumbo (2011) have proposed a systematic validation practice in agreement with this unified and contemporary view of validity. They suggest that, to prove construct validity, different hypotheses should be formulated based on the literature available about the construct the instrument prompts to measure and evidence should be collected to confirm these hypotheses:

1. *Content evidence* consists in developing (or translating) items that the researcher hypothesizes, based on the literature, should represent a specific construct and then asking experts to evaluate the appropriateness of those items.

2. *Score structure evidence* consists in hypothesizing the number of dimensions an instrument should have and confirming this factorial structure. Furthermore, the researcher should prove that each dimension of this instrument measures the construct in a precise and consistent way (reliability evidence).

3. *Generalizability* evidence consists in hypothesizing that the instrument measures the same construct across different subgroups of participants (e.g., gender).

4. *Known groups evidence* consists in comparing the mean level of a test score across groups. Researchers should demonstrate that test scores mean levels are different across these groups in case this difference is expected by the literature.

5. *Convergent* and *discriminant evidence* consists in proving that the test scores of the newly developed instruments are strongly correlated with instruments that, according to the literature, measure the same construct (convergent evidence) as well as that test scores are poorly correlated with instruments that measure a different construct (discriminant evidence).

6. *Criterion-related evidence* consists in demonstrating that the test scores of the newly developed instrument can predict a criterion variable that, according to the literature, should depend on the construct the new instrument aims to measure.

After testing all these hypotheses, the researchers should evaluate whether “all of the accumulated evidence supports the intended interpretation of test scores for the proposed purpose” (Hubley & Zumbo, 2011, p. 220). In other words, if the various kinds of evidence collected confirm the hypotheses suggested by the literature, the researcher can conclude that the instrument measures the constructs it claims to measure (construct validity), at least in the context and sample it was tested on. If a test user aims to use the same instrument in a different context (e.g., country) or sample (e.g., different age range), he/she should prove again the construct validity of the scores obtained from this instrument (i.e., collect new evidence) before interpreting its scores.

This paragraph summarizes how the contemporary view of validity has strongly changed the theoretical assumptions (e.g., validity is contextualized) as well as the practices about validation (e.g., many kinds of evidence need to be collected). It is important to point out that the last decades have also offered psychometricians many new and advanced statistical techniques, which can be adopted in validation practice. According to Zumbo (2005), a class of techniques is particularly central to the contemporary validation process: structural equation models (SEM). The traditional procedures widely utilized the Pearson correlation between observed measures. For example, the correlation between two instruments (e.g., the instrument to validate and a gold standard or a criterion) or between two scores from the same instrument (e.g., test-retest correlation). For the contemporary view of validity, these correlational analyses are useful, but not sufficient (Zumbo, 2005). First, the correlations among observed measures can be substituted with correlations among latent variables, by using SEM, thus excluding the measurement error from the correlation estimate. Furthermore, analyses other than correlations are applied to validate test scores, and all of these can be performed using SEM: for example, CFA, measurement invariance, and composite reliability.

3. Methods

3.1 Procedure

To validate the Italian version of the GREEN scale, we first took care of the item translation and back translation following the suggested guidelines (Geisinger, 1994; van Widenfelt et al., 2005). We then collected content validity evidence by asking experts to evaluate the comprehensibility and representativeness of translated items. Specifically, the translated items were revised by a team of experts in psychometrics and/or psychology of sustainability to evaluate item quality in terms of comprehensibility (i.e., how easy and immediate it is to understand the proposed statement) and representativeness (i.e., how important and coherent the proposed statement is in light of the research objectives previously presented and for each area of investigation). All the items were considered fully adequate, and no further modifications were made.

Once the translated items were approved, we administered them, together with other measurement scales, to a representative sample of 1,002 Italians. This sample was split into two subsamples. The first was adopted to perform an exploratory factor analysis (EFA) and items analysis of the translated items. Once we verified that all items were good and the mono-dimensional structure of the scale was meaningful in the Italian context too, we conducted the validation of the GREEN scale adopting the second subsample. As reported above, the construct validity of a psychometric scale can only be assessed by collecting different kinds of evidence. Hence, a confirmatory factor analysis (CFA) was first performed to collect score structure validity evidence. Omega coefficient and average variance extracted (AVE) were estimated to collect reliability evidence. Then, measurement invariance across genders was assessed to test generalizability evidence.

To test known groups evidence, average values were compared between males and females. Gender differences in pro-environmental behaviors are a well-known phenomenon, because women are more likely to play out environmentally-friendly behaviors (Briscoe et al., 2019; Vicente-Molina et al., 2013, 2018; Xia & Li, 2023). Though gender differences in biospheric values are less explored, existing studies show a similar trend, with women reporting higher levels than men. However, it is worth highlighting that these differences are generally marginal (e.g., Milfont & Sibley, 2016). For instance, a recent cross-country comparison performed in Europe (Sargisson et al., 2020) found only a weak association between gender and biospheric values. Indeed, women are significantly more concerned about protecting the environment, but the difference is small. While this evidence is mainly related to pro-environmental behavior and not specifically to biospheric values, we expected this difference may be reported by the GREEN scale as well.

Subsequently, three structural equation models (SEM) were estimated to obtain convergent, discriminant, and criterion-related validity evidence. For each of the three models, latent variables were considered to remove the measurement error from these validity estimates (Zumbo, 2005). To collect convergent evidence, a correlation between the target scale scores and the scores of a psychometric instrument measuring the same construct should be performed to prove that the two measures are closely related. Consequently, we tested the correlation between the GREEN scale and an instrument (i.e., the UN subscale from the PVQ-RR; Schwartz & Cieciuch, 2022) measuring universalism, namely a personal value reflecting attention to preserving people's welfare and the natural environment (Schwartz et al., 2012). We specifically focused on the measure of universalism-nature (UNN). Because it emphasizes the importance of safeguarding and living in harmony with the natural world, the latent scores of the GREEN scale and the UNN subscale were expected to be strongly associated. To check whether the GREEN scale can discriminate between different constructs (i.e., discriminant evidence), a second correlation model with latent variables was run. In particular, the relationship between biospheric values and connectedness to nature was assessed. This construct refers to how much someone feels a sense of belonging in the natural environment (Lengieza & Swim, 2021). Though related, these two concepts are theoretically distinct. Indeed, differently from biospheric values, which reflect concerns for and importance of nature protection, connectedness to nature has a greater focus on an individual's subjective and emotional experience of oneness with the natural world. Conversely, biospheric values are more abstract and cognitive, functioning as beliefs and guiding principles toward nature preservation (Martin & Czellar, 2017; van der Werff et al., 2013). Accordingly, a significant association between the latent scores of the GREEN scale and the Illustrated Inclusion of Nature in Self scale (IINS; Kleespies et al., 2021) was expected, though with a lower correlation coefficient compared to the convergent one. Finally, the relationship between biospheric values and pro-environmental behaviors was estimated to collect criterion evidence. The literature suggests that values are associated with pro-environmental behaviors and sustainable consumption habits (e.g., De Groot & Steg, 2009). A moderate and positive association between the latent scores of the GREEN scale and the measure for pro-environmental behaviors was thus expected.

3.2 Sample

Data was retrieved from a representative sample of 1,002 Italian individuals, who filled out an online survey in June 2023. Participants were required to give written informed consent. The present study was approved by the Ethical Committee of Catholic University and followed the American Psychological Association (APA) standard ethical guidelines for research. Respondents had to be of legal age (i.e., $\geq$ 18 years old). No other inclusion/exclusion criteria were applied.

To ensure sample representativeness for gender, age, education, and geographical area, a quota sampling procedure was adopted. Females ($n = 500$) accounted for 49.9% of participants. The age of the sample ranged from 18 to 54, with an average of 37.19 years ($SD = 10.94$). Over half of the sample (52%) had a high school diploma, 31.4% of respondents attended university, while the remaining 16.6% had a junior-high school degree. Finally, as for geographical area, 26.4% of participants lived in the north-west of Italy, 19.4% in the north-east, 22.4% in the center, and 31.8% in the southern regions.

Table 1.

Socio-demographic characteristics of the two sub-samples

	Sub-sample 1 (n = 503)	Sub-sample 2 (n = 499)
Gender:		
Males	49.7%	50.5%
Females	50.3%	49.5%
Age	M = 36.69 (SD = 11.06)	M = 37.68 (SD = 10.79)
Education:		
Middle school	15.5%	17.6%
High school	51.7%	52.3%
University degree	32.8%	30.1%

Note. M = Mean; SD = Standard Deviation

For study purposes, respondents were randomly divided into two groups. On the first subsample an exploratory factor analysis and item analysis (n = 503) was performed, while the second one was used to collect validity evidence (n = 499). Table 1 summarizes the sociodemographic characteristics of the two subsamples.

3.3 Measures

Biospheric values were assessed using the GREEN scale. This instrument, developed by Haws et al. (2014), consists of six items rated on a 7-point Likert scale, with answers ranging from 1 (strongly disagree) to 7 (strongly agree). The measure is composed of a single factor and higher scores indicate greater levels of concern for the environment.

To measure nature universalism, the UNN subscale from the Revised Portrait Value Questionnaire (PVQ-RR; Schwartz & Cieciuch, 2022) was adopted. The subscale is formed by three items (ω = .866), estimating individuals' attention to preserve the natural environment (e.g., "It is important to him/her to protect the natural environment from destruction or pollution"). Respondents are asked to express their agreement on a 7-point

Likert scale from 1 = Not like me at all to 7 = Very much like me. Higher scores correspond to higher universalism.

Connectedness to nature was assessed with the IINS, a graphical instrument developed by Kleespies et al. (2021). Two circles, respectively indicating the self and the natural world, are shown as gradually interconnected, representing the degree of perceived connection with nature. Respondents are thus asked to point out the extent to which they feel a sense of oneness with nature by choosing between seven response alternatives. Higher values suggest a stronger connection.

Pro-environmental behaviors were measured by a 6-item scale developed ad hoc. The single-factor scale requires respondents to self-assess the frequency of specific daily environmentally-friendly behaviors across various domains (e.g., “I turn off the lights when I leave a room”). The six items ($\omega = .864$) were designed on a Likert-type scale ranging from 1 (never) to 7 (always).

3.4 Data Analysis

On the first subsample ($n = 503$), descriptive statistics for the six items of the scale were analyzed to evaluate data normality and estimate means and standard deviations. Skewness and kurtosis were controlled, to check that the items fell within the suggested cutoffs. Subsequently, after evaluating the suitability of data by estimating the Bartlett’s test of sphericity ($p < .05$; Bartlett, 1950) and the Kaiser-Meyer-Olkin test (KMO > .50; Kaiser, 1974), an EFA was performed in SPSS 29 using the principal axis factor extraction method. Besides observing the factorial structure, the quality of the items has been evaluated considering factor loadings ($\lambda > .40$; Howard, 2016), extracted communalities, and the corrected item-total correlations.

To collect validity evidence for the Italian version of the GREEN scale, different analyses were performed on the second subsample ($n = 499$). Indeed, following the contemporary view of validity theoretical framework (Hubley & Zumbo, 2011), construct validity of the GREEN scores was demonstrated by testing several types of validity evidence.

As for score structure evidence, a confirmatory factor analysis (CFA) was performed to confirm the single-factor structure of the scale. For this purpose, different indices were considered to evaluate the goodness of fit of the model: the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR) were estimated. Confidence intervals (90%) of RMSEA and χ^2 significance test were also checked, although the latter is largely influenced by sample size (Bentler & Bonett, 1980). RMSEA and SRMR scores lower than .08 indicate a good fit, while a CFI index higher than .90 is considered acceptable (Marsh et al., 2004). Once the mono-dimensional structure of the scale was confirmed, we evaluated the internal consistency of the GREEN scores (reliability evidence) estimating the omega coefficient (ω; McDonald, 1999) and the average variance extracted (AVE; Peterson et al., 2020). Commonly recommended acceptance thresholds are .70 for omega and .50 for AVE (Fornell & Larcker, 1981).

Subsequently, the generalizability of the scale was tested by assessing measurement invariance across genders, to verify whether the factor structure was equivalent between males and females. This type of statistical analysis is aimed at understanding whether a psychometric scale measures a construct with the same meaning for different groups (Putnick & Bornstein, 2016). Multigroup measurement invariance consists of four steps (Vandenberg & Lance, 2000). Configural invariance evaluates whether the factor structure of the scale, the number of factors, and the item-factor correspondence are the same across groups. Secondly, through weak invariance, the similarity of factor loadings between groups was evaluated. Strong invariance tests the equivalence of item intercepts, while strict invariance assesses the equivalence of residual errors (Brown et al., 2017). The four models of invariance were compared adopting the free baseline approach (Stark et al., 2006). Specifically, the weak model was compared with the configural model, and the strong model was compared with the weak model. Finally, strict and strong models were compared. To check measurement invariance, CFI and RMSEA differences between models were evaluated, because χ^2 significance test is biased by sample size. As suggested by Chen (2007), a decrement of the CFI index higher than .01 suggests a meaningful decline of the model fit, as well as a decrease higher than .015 for the RMSEA index. After verifying that the scale was comparable between male and female participants (i.e., sufficient levels of measurement invariance), we compared the latent factor mean levels of GREEN across gender groups to test whether the differences expected according to the literature were detectable using the GREEN scale as well (known groups evidence). We expected females to have a higher level of biospheric values as suggested by Sargisson et al. (2020).

To check for convergent and divergent evidence, the scale was evaluated for association with other variables. Specifically, to collect convergent evidence a correlation model with latent indicators was performed, considering both the GREEN scale and UNN subscale from the PVQ-RR (Schwartz & Cieciuch, 2022). Instead, discriminant evidence was tested by performing a second correlation model with the GREEN scale and the IINS graphical measure. Latent indicators were considered in the model as well. Finally, as for criterion-related evidence, the predictive validity of the GREEN scale was evaluated by performing a regression model with latent indicators. The capability of the scale scores to predict the scores of the ad hoc measure for pro-environmental behaviors was thus tested. The goodness of fit for each of the three SEM was evaluated considering the following indices: χ^2 significance test, RMSEA, CFI, and SRMR.

4. Results

4.1 First Subsample: Item Analysis, EFA, Reliability

The first subsample was composed of 503 participants. Both skewness and kurtosis reported a normal distribution of the six items (with skewness values ranging from –.82 to –.60 and kurtosis values ranging from –.097 to .504). After checking for normality distribution, an EFA was performed. The Barlett's test of sphericity and the KMO measure of sampling adequacy provided satisfactory results. The Bartlett's test was significant: χ^2 = 1,746.76 (*df* = 15, p < .001) and the KMO was .902. The eigenvalue criteria suggested a single-factor structure for the scale. Factor loadings exceeded the suggested cut-off, with λ values ranging from .743 to .814. As reported in Table 2, extracted communalities were higher than .50 and the corrected item-total correlation values were all above .70. Finally, the single-factor structure explained the 61.62% of the total variance. The composite reliability of the scale was also good (ω = .906).

4.2 Second Subsample: Collecting Validity Evidence

4.2.1 Score Structure and Reliability Evidence

The CFA performed on a subsample of 499 respondents indicated that the single-factor theoretical model had good fit indices: χ^2 = 13.501, *df* = 9, p = .141; RMSEA = .032, 90% CI [.000, .064]; CFI = .992; SRMR = .021. The goodness of the model was also confirmed by the high factor loadings of the items (λ values ranging from .716 to .825), which resulted significant for p < .001 (see Table 3). Finally, internal consistency scores (ω = .901; AVE = .603) suggested that the scale was reliable as well.

Table 2.

Descriptive statistics and items factor loading for the EFA

	M	SD	Skewness	Kurtosis	Factor loading	Extracted communality	Item-total correlation
Item 1	5.29	1.44	-0.783	.504	.779	.607	.734
Item 2	5.09	1.58	-0.771	.228	.814	.663	.766
Item 3	4.81	1.62	-0.604	-0.097	.794	.630	.750
Item 4	5.21	1.57	-0.818	.377	.743	.552	.702
Item 5	5.24	1.41	-0.770	.488	.775	.601	.732
Item 6	4.83	1.56	-0.639	.107	.802	.643	.755

Note. EFA = Exploratory Factor Analysis; M = Mean; SD = Standard Deviation.

4.2.2 Generalizability and Known Groups Evidence

The results of the multigroup CFAs showed a good fit of the model along the four steps of the measurement invariance (i.e., configural, weak, strong, and strict invariance). Specifically, the difference in the χ^2 statistic was always nonsignificant, and differences in CFI and RMSEA indices when comparing models were below the suggested cutoffs (i.e., ΔCFI < .01; ΔRMSEA < .015), thus confirming that the factor structure of the scale was equivalent across genders. Table 4 indicates models fit along the four measurement invariance models.

The comparison to detect differences on the scores of the scale across genders turned out to be nonsignificant (p = .113). In particular, the mean level of biospheric values reported by women was higher than the one reported by men when looking at both latent scores (M_{female} = .00; M_{male} = –.15) and observed scores (M_{female} = 5.18, SD = 1.23; M_{male} = 4.99, SD = 1.17), but this difference was not statistically significant.

Table 3.

Descriptive statistics and items factor loading for the CFA

	M	*SD*	Skewness	Kurtosis	Factor loading
Item 1	5.22	1.39	-0.645	.408	.819***
Item 2	5.05	1.45	-0.588	.110	.825***
Item 3	4.77	1.55	-0.467	-0.226	.786***
Item 4	5.22	1.51	-0.818	.420	.740***
Item 5	5.25	1.44	-0.802	.571	.716***
Item 6	5.00	1.46	-0.633	.144	.771***

Note. CFA = Confirmatory Factor Analysis; M = Mean; SD = Standard Deviation; *** $p < .001$.

4.2.3 Convergent, Divergent, and Criterion-Related Evidence

Convergent, divergent, and criterion-related evidence was tested by performing three different SEM using latent variables as indicators to remove the measurement errors from these validity estimates.

Convergent evidence. The correlation model between biospheric values and universalism reported good fit indices: $\chi^2 = 41.788$, $df = 26$, $p = .026$; RMSEA = .035, 90% CI [.012, .054]; CFI = .986; SRMR = .026. Furthermore, biospheric values resulted significantly and positively associated with universalism ($r = .864$, $p < .001$). Pearson's correlation was in the expected direction and with a strong effect size, confirming convergent evidence.

Discriminant evidence. Fit indices indicated that the correlation model between biospheric values and connectedness to nature was good: $\chi^2 = 19.089$, $df = 14$, $p = .162$; RMSEA = .027, 90% CI [.000, .054]; CFI = .993; SRMR = .021. The estimated model showed a significant and positive relationship between the two variables ($r = .452$, $p < .001$). As expected, the correlation coefficient between biospheric values and connectedness to

Table 4.

Fit indices for the invariant model

	χ^2	*df*	p	RMSEA (90% CI)	CFI	SRMR	$\Delta_{\chi 2}$	Δ_{df}	p	Δ_{CFI}	Δ_{RMSEA}
Configural	25.043	18	.124	.040 (.000 .074)	.988	.031					
Weak	30.851	23	.127	.037 (.000 .068)	.987	.046	4.599	5	.467	-0.001	-0.003
Strong	36.094	28	.140	.034 (.000 .063)	.986	.045	3.740	5	.587	-0.001	-0.003
Strict	47.187	34	.066	.039 (.000 .065)	.978	.071	10.066	6	.122	-0.008	.005

Note. χ^2 = chi-square; *df* = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residuals.

nature (i.e., discriminant evidence) was weaker than that between biospheric values and universalism (i.e., convergent evidence). This finding confirmed the discriminant evidence of the scale.

Criterion-related evidence. The full regression model with biospheric values predicting pro-environmental behaviors resulted adequate: $\chi^2 = 92.905$, $df = 53$, $p = .001$; RMSEA = .039, 90% CI [.025, .052]; CFI = .975; SRMR = .046. Values were found to be a strong and positive predictor of pro-environmental behaviors ($\beta = .515$, $p < .001$), thus highlighting the presence of criterion-related evidence. Furthermore, biospheric values explained almost a quarter of the total variance of pro-environmental behaviors ($R^2 = .265$).

5. Discussion

The present paper aimed to validate the Italian version of the GREEN scale, developed by Haws and colleagues (2014) following the guidelines of the contemporary view of validity. This approach has two major advantages. First, it does not rely on a single type of validity to validate an instrument, but, instead, collects multiple pieces of evidence to prove that the instrument under study does indeed measure the construct it is expected to measure. Second, this evidence is gathered using state-of-the-art statistical techniques that allow measurement error to be removed from the estimates. In summary, conclusions drawn using the contemporary view of validity approach are more reliable.

Findings supported the unidimensionality of the scale and its factorial invariance across genders. Indeed, the EFA replicated the original factorial structure of the scale and the CFA provided good fit indices for the theoretical model. The measurement invariance across genders also supported that the single-factor measure of biospheric values was equivalent between males and females. However, we did not find the expected gender differences in the average scores of biospheric values. As stated in the Introduction, the literature on this topic is still limited and not univocal. Indeed, while gender differences in pro-environmental behaviors are a well-known phenomenon, the few previous studies on biospheric values reported only a marginal variability between men and women (e.g., Sargisson et al., 2020). This could suggest that the gender difference is present at a behavioral level, but less marked in its antecedents, such as values. We also argue that, nowadays, climate change and environmental issues are gaining more and more emphasis in our lives. Hence, the marginal gender differences found in the present study might also be explained by the increase of public attention on the phenomenon.

Furthermore, convergent, discriminant, and criterion validity evidence were supported, because biospheric values were significantly related to universalism (UNN from PVQ-RR; Schwartz & Cieciuch, 2022), connectedness to nature (IINS; Kleespies et al., 2021), and pro-environmental behaviors, respectively. Specifically, the high correlation between the scores of the GREEN scale (i.e., biospheric values) and UNN subscale (i.e., universalism) suggested that the two instruments measure the same psychological construct. On the other hand, the relationship between biospheric values and connectedness to nature was significant, though with a smaller effect size compared to the correlation between biospheric values and universalism. This highlighted that the GREEN scale and the IINS measure two different and separate constructs. Finally, biospheric values significantly predicted daily environmentally-friendly behaviors, confirming the idea that people's beliefs and principles may explain people's behaviors (e.g., Wang et al., 2021).

In brief, the GREEN scale proved to be a valid and reliable measure for biospheric values in the Italian context. In agreement with the contemporary view of validity, we can conclude that when this scale is used in a context (e.g., Italian) and with a sample (e.g., people over 18 years old) similar to the one adopted in the current study, users can rely on test scores to make inferences about biospheric values. When, instead, the measure is adopted in a different context or with a different sample, test users should first collect new evidence to be sure that the instrument measures what it is supposed to measure.

This study does not lack limitations. First, considering its cross-sectional nature, any inference on the causal relationship between biospheric values and environmentally-friendly behaviors should be avoided. Future research should adopt a longitudinal design to overcome this limit and test the predictive version other than the concurrent version of the criterion-related validity. Moreover, self-reported measures for pro-environmental behaviors should be somehow biased by social desirability and other response biases. Behavioral data should also be considered when investigating the role of biospheric values in shaping individuals' actions toward the natural environment. A third methodological limit refers to the absence of a multitrait-multimethod matrix (MTMM) analysis usually adopted to assess the convergent and discriminant evidence of the scale (Campbell & Fiske, 1959). Because in our study all the variables were measured using the same method (i.e., self-report assessment) we could not collect this more complete evidence of convergent/discriminant validity, but we had to test them separately using a single correlation coefficient. Fourth, the known groups evidence of the scale was not supported (i.e., the expected difference between women and men was present at a descriptive level but not statistically significant). Future studies should better investigate gender differences in biospheric values, considering that the current literature is still limited and discordant. Finally, another limitation of our study is the lack of inclusion of elderly individuals, which may affect the generalizability of our findings. Given that older adults might have different attitudes toward environmental issues, possibly due to a shorter time horizon or a more intrinsic concern for long-term sustainability, future research should explore these differences within biospheric values to provide a more comprehensive understanding.

CHAPTER 3

IN SEARCH OF SOCIALLY RESPONSIBLE INVESTORS: A LATENT PROFILE ANALYSIS

As previously reported, the profile of socially responsible investors and the motivations behind their decision to invest responsibly have received little attention so far (Garg et al., 2022). Considering the relevance of the topic and the lack of systematic research on the typical profile of sustainable investors, the present study aims at identifying the distinctive characteristics of socially responsible investors. A conceptual model, rooted in the Theory of Planned Behavior, was developed and investigated by adopting a person-centered approach. Specifically, a Latent Profile Analysis was performed to classify the sample in subgroups characterized by different combinations of the variables considered in the model (i.e., clusters). Since human behavior is the result of a series of factors that interact with each other, a person-centered approach provides insightful hints to understand how specific configurations of variables are associated with the outcome. In particular, once participants are divided into different groups, each characterized by a specific configuration of the variables under investigation, these different profiles can then be associated with an outcome variable to identify the profile(s) that best predict the desired outcome. Hence, our purposes were: (i) identifying different profiles of consumers in a representative sample of Italian consumers; (ii) verifying which profile(s) is more likely to be a current and/or potential socially responsible investor.

The chapter is structured as follows. Section 1 describes the theoretical framework and supplies the conceptual model developed in the study. Then, a presentation of the statistical approach adopted in the study is included in Section 2. Methodology and results of the study are presented respectively in Section 3 and 4. Findings are discussed in Section 5, while Section 6 finally shows the limits of the study.

1. Theoretical framework and conceptual model

Many researches aimed at defining the typical profile of socially responsible investors merely considered socio-demographic characteristics. Evidence from these studies suggested that socially responsible investors are primarily women and well-educated individuals (e.g., Gutsche & Zwergel, 2020; Roos et al., 2024; Rossi et al., 2019). There is instead a lack of agreement about the mean age of sustainable investors, as some studies suggested that older individuals are more likely to invest in SRI (e.g., Delsen & Lehr, 2019), while others reported that younger individuals prefer to invest responsibly (e.g., Bauer & Smeets, 2015).

However, socially responsible investors' profiles cannot be completely described by socio-demographic variables alone, as they have less explanatory power than attitudinal and psychological variables (Dorfleitner & Utz, 2014; Wins & Zwergel, 2016). In this direction, other studies focused instead on socially responsible investors’ motivations, attitudes, and psychological characteristics (Apostolakis et al., 2016; Pérez-Gladish et al., 2012; Riedl & Smeets, 2017; Williams, 2007). On fact, the assumptions of classical financial models have been put in crisis by SRI. Sustainable investors do not behave as expected by traditional financial theories. Indeed, they are not necessarily profit oriented and do not focus merely on the financial performance of their investments. Rather than considering only risk-return tradeoffs, socially responsible investors are guided also by prosocial and pro-environmental attitudes and ethical values in their investment decisions (Bauer & Smeets, 2015; Brodback et al., 2019; Gamel et al., 2016). Evidence showed that investors are often willing to invest in accordance with their ethical values, even if it means paying higher fees or gaining lower returns on their investments (Apostolakis et al., 2018a; Gutsche & Ziegler, 2019). As well, by leveraging also on personal values and ethical dimensions, SRI might potentially attract new investors and encourage participation in capital markets (Rossi et al., 2019). At the same time, it should be acknowledged that while SRI is often seen as diverging from the traditional risk-return maximization framework, investors may choose sustainable investments for reasons beyond ethical considerations. For instance, some might perceive them as potentially outperforming traditional funds, while others may invest in SRI to diversify their portfolios. Additionally, some investors may opt for SRI for both ethical and economic reasons. The motivations behind sustainable investing remain a subject of ongoing debate in the literature and deserve greater attention in future studies on sustainable investment decisions.

The purpose of the present study was to investigate the determinants and, specifically, which configuration of these determinants (i.e., which profile) is associated with socially responsible investing. We developed a model inspired by the Theory of Planned Behavior (TPB), which is a revisitation of the Theory of Reasoned Action (Ajzen & Fishbein, 1980). TPB has been widely used to explore and explain individual's behavior in various research fields (Kwon & Silva, 2020). According to TPB, three main variables (i.e., attitudes, subjective norms, perceived behavioral control) are responsible for the formation of behavioral intention, which in turn leads to actual behavior. Attitudes refer to the beliefs and valence of a certain behavior. Subjective norms reflect individuals' perception about social pressure and the tendency to comply with significant others' expectations. Finally, perceived behavioral control describes the extent to which individuals perceive ease or difficulties in the performance of a specific behavior (Ajzen, 1991).

Despite being one of the most common theories on consumer behavior, TPB was subject to various critiques throughout the years, such as for "being too narrow and rational, and lacking the inclusion of variables related to people's moral values" (Rozenkowska, 2023, p. 3). However, as stated by Ajzen himself (1991), the main strength of TPB lies on its flexibility and capacity to be adapted to various research contexts and expanded by including additional constructs to better understand human behavior. Therefore, we opted for the model of TPB as theoretical framework, adapting it to the field of SRI.

To the best of our knowledge, only a few studies (e.g., Apostolakis et al., 2018b) adopted TPB to explain the decision to invest responsibly. While previous studies have already adopted the TPB as a theoretical framework to explain socially responsible investing, our study differentiates itself by extending the TPB by incorporating overlooked dimensions that may play a crucial role in SRI, such as personal values, as well as factors typically associated with investment choices, including financial literacy and risk tolerance. Secondly, rather than employing a variable-centered approach, this study adopts a person-centered perspective, focusing on how these variables interact with each-other, to define the identikit of socially responsible investors.

For study purposes, we adapted and extended the Theory of Planned Behavior to explain socially responsible investing. In particular, besides the determinants suggested by the TPB (i.e., attitudes, subjective norms, perceived behavioral control), we investigate a set of different variables with the aim to also include in our framework: 1) determinants suggested by the classic literature on investment decision making; 2) determinants suggested by recent literature specifically focused on socially responsible behaviors. A brief review of the variables included in the proposed model is reported below.

1.1 Determinants of TPB

1.1.1 Attitudes towards SRI

Various studies (e.g., Jonwall et al., 2023) suggested a significant role of consumers' attitude on SRI and their decision to invest responsibly. For instance, Apostolakis et al. (2018b) reported that positive attitudes towards SRI predicted pension beneficiaries' intention to hold portfolios composed of socially responsible products. In the present study, two different attitudes towards SRI were investigated: perceived consumer effectiveness and consumers' trust.

Literature reported that perceived consumer effectiveness plays a key role in sustainable investment decisions (e.g., Vyas et al., 2022). This variable refers to the belief that individuals can have a positive influence and impact on the environment through their pro-environmental behaviors or sustainable consumption habits. As for SRI, perceived effectiveness reflects the extent to which consumers believe that SRI can address or resolve environmental and social issues. The association between perceived effectiveness and investing in responsible financial assets was highlighted by various authors (e.g., Garg et al., 2022; Palacios-González & Chamorro-Mera, 2018; Wins & Zwergel, 2016).

The role of trust in SRI was previously considered by a few studies, which investigated whether consumers' skepticism might prevent investors from socially responsible investing. As previously reported, there is still a lack of transparency and convergent validity between various ESG ratings, and this issue might undermine consumers' trust towards SRI. For instance, a recent study by Avramov et al. (2022) found that uncertainty about ESG ratings reduced the demand for responsible financial assets. However, studies that directly investigated perceived trust in SRI provided mixed results. While some (Nilsson, 2008; Wins & Zwergel, 2016) could not conclude that trust significantly affected the decision to invest responsibly, Gutsche and Zwergel (2020) found that distrust was a strong barrier for socially responsible investing. The role of consumers' trust towards sustainable investment products is still not completely clear. However, we argue that it could be a relevant issue for those attracted by SRI.

1.1.2 Personal norms

Even though the TPB mainly focused on subjective norms, namely the perceived social pressure to engage in a specific behavior, only a few studies (Apostolakis et al., 2018b;

Gutsche et al., 2019) investigated the impact of subjective norms on socially responsible investing, suggesting a positive relationship between the two. Literature on socially responsible investors investigated mainly how personal norms influence sustainable investment decisions. Therefore, in the present study, we focused on personal norms as well. As stated by Shwartz (1973), personal norms can be conceived as a personal standard of behavior, rather than a standard from social groups, which characterizes subjective norms. Furthermore, personal norms are described as internalized social norms. Previous findings highlighted that those individuals with great altruistic, prosocial, and pro-environmental values were also more likely to invest in SRI (Garg et al., 2022; Roos et al., 2022). On the contrary, evidence suggested that materialistic and egoistic values were negatively related to socially responsible investing (Brodback et al., 2019; Singh et al., 2021; Vyas et al., 2022).

1.1.3 Perceived behavioral control

In the present study, the concept of perceived behavioral control concerns the extent to which individuals perceive control over the environment. In other words, it reflects either the belief that through our actions we can effectively tackle climate change, or a fatalistic sense of helplessness that environmental issues are beyond human control. Indeed, climate change is one of the biggest issues that mankind is going to face, and some individuals might assume negative beliefs about how humans can effectively fight it. Perceived control on the environment could prompt individuals' pro-environmental behaviors (Giefer et al., 2019; Hosta & Zabkar, 2021). For instance, Cleveland et al. (2020) found that the perception of having the ability to affect the environment motivates individuals in conservation and recycling behaviors and to adopt sustainable consumption habits. A significant association between perceived behavioral control and sustainable consumption was found by Patel et al. (2020) as well. Perceived behavioral control is thus expected to shape socially responsible investing as well.

1.2 Classical determinants of investment decision making

Literature about investment decision making has stressed the importance that knowledge in the financial domain (e.g., Thomas & Spataro, 2018) and financial risk tolerance (e.g., Keller & Siegrist, 2006) have in predicting the decision to invest. For this reason, in the current study we investigated both consumers' knowledge in the financial domain in general (financial literacy) and about sustainable investments specifically (perceived knowledge on SRI), as well as consumer's risk tolerance. Since these determinants might also affect socially responsible investing (e.g., Wins & Zwergel, 2016; Riedl & Smeets, 2017), they were considered as well in our conceptual model.

1.2.1 Financial literacy and SRI knowledge

Financial literacy is univocally considered one of the main predictors of investment decisions. Defined as a combination of knowledge, skills, attitude, and behavior necessary for good financial decision making (OECD, 2013), it is associated with financial market participation and significantly affects portfolio composition and diversification (Bannier & Neubert, 2016; Hermanoss & Jonsson, 2021; Hsiao & Tsai, 2018). Though widely investigated in conventional investment decision making, the role of financial literacy in socially responsible investing is still quite overlooked. Some findings highlighted the key role of financial literacy in investors' information search process for SRI (Nilsson et al., 2010; Shanmugam et al., 2022). However, the relevance of financial literacy in actual investment decisions is less clear. Borges and Pownall (2014) reported a significant effect of financial literacy in shaping the decision to invest responsibly, arguing that a lack of literacy might be a barrier, as SRI require the consideration of both financial and ethical information in the investment decision process. However, other studies reported a negative relationship between financial literacy and socially responsible investing (Brunen & Laubach, 2022; Rossi et al., 2019). Though the relevance of financial literacy in socially responsible investing is still debated, perceived knowledge on responsible investment products prompts consumers to invest in SRI (Jonwall et al., 2023; Wins & Zwergel, 2016). Gutsche and Zwergel (2020) suggested that since responsible investment products are more complex than conventional ones, individuals lacking proper knowledge would pay too high information cost. Therefore, they would be less likely to invest responsibly due to difficulties in searching for information on SRI. To measure consumers' knowledge, both financial literacy and knowledge on SRI have been considered in our model.

1.2.2 Financial risk tolerance

Another determinant influencing investment decision making refers to financial risk tolerance, as investing inherently involves assuming risks. Previous studies highlighted that risk appetite affects both financial market participation and portfolio composition (Grable, 2016). However, the influence of risk tolerance in socially responsible investing is less clear. Indeed, some studies highlighted a significant association (Bauer & Smeets, 2015; Gutsche et al., 2021; Riedl & Smeets, 2017), whereas others found that risk appetite is incapable of explaining socially responsible investing (e.g., Apostolakis et al., 2018b; Hafenstein & Bassen, 2016). Various explanations were proposed to justify these findings. Some scholars call in cause differences in consumers' risk perception of sustainable investment products. For instance, Wins and Zwergel (2016) hypothesized that investors might perceive sustainable investment products as risky as conventional financial assets. As well, Delsen and Lehr (2019), reported that risk appetite did not significantly contribute to the understanding of sustainable investment decisions. They argued that risk tolerance could be a great predictor in the traditional investment literature, as it generally clarifies the different preferences for the risk-return tradeoff. However, its contribution to the understanding of socially responsible investing is quite marginal, since other variables, such as value orientation, could make a difference.

1.3 Determinants of socially responsible behaviors

Literature highlighted that other variables may come into play in pro-environmental behaviors and sustainable consumption practice. Specifically, environmental concern (e.g., Tam & Chan, 2017) and a sense of connection to nature (e.g., Barbaro & Pickett, 2016) are able to stimulate environmental-friendly behaviors. Therefore, we included also these two variables as determinants of socially responsible investing. By adding these variables, we were able to get a greater focus on environmentalist attitudes, like previous studies (e.g., Seifert et al., 2024).

1.3.1 Environmental concern

Concerns for environmental and climate change problems could prompt individuals to play out more sustainable behaviors and consumption habits (Yang et al., 2020). Studies showed that those more aware about environmental issues are more likely to purchase sustainable and environmental-friendly products (Lin & Niu, 2018; Zameer & Yasmeen, 2022). A similar trend could be found for socially responsible investing. An interest in environmental and social issues generally results in the decision to invest responsibly (Gamel et al., 2016; Jansson et al., 2014; Williams, 2007). When they are required to choose for responsible mutual funds, investors tend to not focus solely on financial aspects, like past performances and riskiness. Instead, they search for detailed information on screening criteria, or the guidelines adopted for social responsibility (Nilsson et al., 2010). Likewise, Gutsche and Ziegler (2019) reported that environmental concern was associated with the willingness to sacrifice returns by choosing responsible investment products rather than their conventional counterparts. In line with earlier findings, we included environmental concerns in our conceptual model.

1.3.2 Connectedness to nature

Connectedness to nature refers to the capacity of self-transcendence, in which individuals overcome their personal boundaries and feel a sense of connection with nature. In other words, it reflects the extent to which individuals perceive to belong to the natural world (Lengieza & Swim, 2021). Previous studies (e.g., Barbaro & Pickett, 2016) showed that a sense of belongingness to nature was associated with pro-environmental behaviors. Similarly, Dong et al. (2020) reported that a stronger feeling to be part of the natural environment led individuals to a higher likelihood of sustainable consumption behaviors. In line with the studies previously reported, this characteristic is expected to shape the decision to invest in socially responsible products as well.

2. Finite mixture models

Clustering refers to the classification of cases into different subsets, according to data patterns. Overall, cases sharing similar characteristics are grouped together. On the contrary, dissimilar configurations of data are clustered in different sub-groups (Rokach & Maimon, 2006).

Finite mixture models attracted more and more attention in recent times. By this term, we mean a group of statistical techniques rooted in a person-centered approach, as well as classical clustering techniques (e.g., K-means cluster analysis). The purpose of variable-centered approaches is to find relationships between variables in a population, for instance by estimating correlations or regressions (Howard & Hoffman, 2018). On the other hand, through a person-centered perspective, it is possible to classify individuals in terms of different patterns (or configurations) that variables might exhibit (i.e., clustering). Hence, this approach assumes that various sub-groups exist within the sample, each one showing a specific pattern for the variables considered (Bauer, 2022; Ferguson et al., 2020). Furthermore, the purpose of these analytical techniques consists in grouping together individuals reporting similar response patterns and thus creating heterogenous clusters. This approach is best suited for investigating whether different subpopulations exist within a population.

Considering that human behaviors and decision-making processes are quite complex and various determinants are involved, this perspective could be useful in research field related to behavioral sciences, such as psychology or economics. Indeed, it could be assumed that human behavior is the result of a series of factors interacting with each other. Therefore, through a person-centered approach, researchers can understand how variables interplay with each other and influence the final behavior.

These statistical techniques allow researchers to identify unobserved latent subgroups within a sample, based on different response patterns of observed variables. Conceptually, finite mixture models are like dimensionality reduction techniques and, especially, factor analysis. Indeed, while factor analysis groups items with an underlying common latent factor, mixture models groups homogenous individuals under the same cluster.

Among mixture models, Latent Class Analysis (LCA) and Latent Profile Analysis (LPA) are the most known and simplest statistical techniques. Both of them are suited for cross-sectional data, though longitudinal LCA and LPA exist as well (Nylund-Gibson & Choi, 2018). The main difference between LCA and LPA consists in the types of indicators used. Indeed, while the former is used for categorical and/or binary data, the latter requires continuous variables (Bauer, 2022).

Within clustering techniques, finite mixture models are promising tools, showing various advantages in comparison to other clustering statistical analyses. First of all, rather being atheoretical and data driven as classical clustering techniques, mixture models assume a theoretical model, thus requiring researchers to accurately evaluate which indicators include in the model. Indeed, they assume an underlying categorical latent factor (i.e., the membership of a specific sub-group) explaining differences in response patterns (Sinha et al., 2021). In other words, statistical techniques such as LCA or LPA are model-based and handle cluster membership as a latent variable. Since behavioral sciences are generally interested in developing and testing theoretical models, such statistical techniques have a great potential in the field.

Secondly, these statistical techniques allow a mathematical evaluation of the estimated models, through fit indices, thus facilitating the selection of the correct number of latent subgroups included within a population. Mixture models also provide individuals' classification probability for each sub-group. As previously reported, conversely to traditional clustering methods, they conceive group membership as a latent variable, where its score represents the probability of belonging to a specific sub-group. This feature enables researchers to account for classification uncertainty, which is not estimated by traditional cluster analysis techniques (Nylund-Gibson & Choi, 2018; Spurk et al., 2020), thus helping in the evaluation of the classification quality (Sinha et al., 2021).

3. Methods

3.1 Sample

Cross-sectional data stem from an online survey, developed and administered in June 2023 to a representative sample of 1,002 Italian consumers. The questionnaire was distributed via Qualtrics online survey platform. Participants were recruited through e-mail invitations and received monetary compensation as an incentive for study participation. 1,120 individuals were originally contacted for the study, with a response rate of 89.5%. Survey completion required about 15 minutes. A written informed consent was obtained from respondents before they started the questionnaire. The Università Cattolica del Sacro Cuore Ethical Committee approved the current study, which adhered to the American Psychological

Association (APA) standard ethical guidelines for research. Respondents had to be of legal age (i.e., ≥ 18 years old). No other inclusion/exclusion criteria were used.

A quota sampling method was adopted to check sample representativeness for gender, age, education, and geographical area. The sample was equally distributed for gender (49.9% female). Participants' ages ranged from 18 to 54 years old, with a mean age of 37,19 years (*SD* = 10.94). As for education, 16.6% had a middle-school degree, while most respondents (52%) had a high-school diploma. The remaining 31.4% attended university. Referring to geographical area, 45.8% of participants lived in the north, specifically 26.4% in the north-west and 19.4% in the north-east. 22.4% lived in central parts of Italy, while the remaining 31.8% lived in the south. Socially responsible investors accounted for only 4.7% of the entire sample. The share of socially responsible investors within the sample is in line with previous inquiries on the Italian population (e.g., Petrillo et al., 2016).

3.2 Measures

3.2.1 Determinants of TPB

3.2.1.1 Attitudes toward SRI. In the present study, two attitudes towards SRI were investigated: perceived consumer effectiveness and trust.

Perceived consumer effectiveness was estimated specifically for SRI domain (e.g., "*By investing in socially responsible products, every investor can have a positive impact on the environment*"). Four items were developed on a Likert scale, ranging from 1 (I totally disagree) to 7 (I totally agree).

Trust on SRI was measured through a single statement representing consumers' confidence that socially responsible products consider only companies effectively respecting social and environmental sustainability ("*I am confident that socially responsible products include only those companies concerned about environmental and social sustainability*"). The item was developed on a seven-step Likert scale (1 = I totally disagree; 7 = I totally agree).

3.2.1.2 Personal norms. Personal norms were operationalized by using the Italian adaptation of GREEN Scale (Haws et al., 2014) presented in Chapter 2. This instrument reflects consumers' effort to adopt sustainable lifestyles and habits (e.g., "*I consider the potential environmental impact of my actions when making many of my decisions*"). The single-factor psychometric scale consists of six items, developed on a Likert scale ranging from 1 (I totally disagree) to 7 (I totally agree).

3.2.1.3 Perceived behavioral control. Perceived behavioral control was measured by four items created ad hoc for the present study (e.g., "*I am convinced that my actions and behavior can make a difference in facing climate change*"). The items were developed on a Likert-type agreement scale ranging from 1 (I totally disagree) to 7 (I totally agree).

3.2.2 Classical determinants of investment decision making

3.2.2.1 Financial literacy. Financial literacy was assessed through four questions concerning investment domain. Specifically, the "Big Three" developed by Lusardi and Mitchell (2011) were used to measure individuals' knowledge about interest rates, inflation, and risk diversification. Furthermore, an additional question was retrieved from Robba et al. (2024) to assess the understanding of the risk-return trade-off ("*There is a direct link between risk and the return on a financial asset, so an investment with a high expected return is probably very risky.*"). Participants were asked to report whether that statement was true or false. A general index of financial literacy was then obtained by adding the number of correct answers. The total score ranged between 0 (no correct answers) and 4 (all answers correct).

3.2.2.2 Perceived knowledge on SRI. Perceived knowledge on SRI was measured with a single ad hoc statement: "*How would you assess your knowledge on SRI?*". The item was developed on a Likert scale, ranging from 1 (I have never heard about that) to 7 (I have great knowledge about that).

3.2.2.3 Financial risk tolerance. Risk tolerance was measured through five items. Three out five of the items were retrieved from Kapteyn and Teppa (2011), while the remaining two items were developed ad hoc for the survey. The five items measure individuals' risk appetite specifically in financial and investment domains (e.g., "*I get more and more convinced that I should take greater financial risks to improve my financial position*").

3.2.3 Determinants of socially responsible behaviors

3.2.3.1 Environmental concern. Individuals' concern for climate change issues was measured through six items developed on a seven-point Likert scale (1 = I totally disagree; 7 = I totally agree). The items were created ad hoc for the study and refer to a single factor (e.g., "*Climate change is pushing the planet to a point of no return*").

3.2.3.2 Connectedness to nature. To assess perceived connectedness to nature, the Illustrated Inclusion of Nature in Self scale (IINS; Kleespies et al., 2021) was adopted. The IINS is a graphical tool which consists of two circles: one represents the self, while the other stands for the natural environment. The two circles are presented gradually interconnected, metaphorically indicating the extent to which individuals feel a sense of oneness with nature. Respondents were thus asked to report the perceived degree of connection between them and the natural world. Higher values suggest a stronger connection.

3.2.4 Socially responsible investing

To identify current responsible investors, respondents were required to indicate whether they owned SRI products at the time of the survey. Hence, we obtained a dummy variable (0 = not investing in SRI and 1 = currently investing in SRI). Furthermore, respondents were also asked to report their willingness to invest responsibly in future. After a brief explanation about SRI, participants had to answer this statement: "*Would you consider investing your money in sustainable investment products in the next six months?*". For those who were already sustainable investors, the statement was slightly different, as it was asked whether they considered additionally investing in socially responsible financial assets. Answers ranged on a seven-point Likert scale (1 = certainly not; 7 = certainly yes).

3.3 Data analysis

To understand which psychological profiles were associated with the decision to invest in SRI, we had to 1) identify the profiles present in our sample through a Latent Profile Analysis, and, then, 2) assess the association between these profiles and socially responsible investing decision.

Before performing the Latent Profile Analysis, Confirmatory Factor Analyses (CFA) were performed to check the factorial structure of the psychometric scales considered in the study. Furthermore, the CFA enabled us to save the factor scores of the measures and include in the Latent Profile Analysis a more reliable estimate of the variables.

3.3.1 Latent Profile Analysis

To identify the groups that best describe the heterogeneity within the current sample, we performed a Latent Profile Analysis (LPA). Determinants suggested by classical literature on investment decision making (financial literacy, perceived knowledge on SRI, financial risk tolerance), determinants suggested by the TPB (perceived consumer effectiveness, trust, personal norms, perceived behavioral control), as well as determinants suggested by recent studies on socially responsible behavior (environmental concern, connectedness to nature) were included as observed indicators. We examined fit indices of measurement models, beginning with one class and adding classes incrementally. We stopped estimating additional classes when the LPA solution generated groups with a too small sample size (< 5%; Masyn, 2013).

As suggested by Sorgente et al. (2019), selecting the optimal fitting model(s) was based on both inferential and descriptive relative fit indices. The statistical tests that were adopted as *inferential* measures of relative fit indices are the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT; Vuong, 1989; Lo et al., 2001) and the adjusted Lo-Mendell-Rubin likelihood ratio test (adjusted LMR-LRT; Lo et al., 2001). These tests compare a (k-1)-class model with a k-class model; a statistically significant p-value suggests that the k-class model fits the data significantly better than a model with one less class. Conversely, if it is not significant, the k-class model is as good as the (k-1)-class model, so the (k-1)-class model is preferred according to parsimony criterion.

As *descriptive* measures of relative model fit, five information criteria (IC) were used. Specifically, the Akaike information criterion (AIC), the Consistent Akaike Information Criterion (CAIC), the Approximate Weight of Evidence (AWE), the Bayesian Information Criterion (BIC) and the Sample-size Adjusted Bayesian Information Criterion (SABIC). Smaller IC values indicate better fit.

Once the best model is selected, the quality of its classification (i.e., assignment of people to profiles) had to be evaluated (Masyn, 2013). The most common diagnostic classification is entropy (E_k), where values closer to 1 indicate a better classification of cases. Furthermore, the quality of the classification is evaluated by checking the class proportion (CP_k or π_k), the modal class assignment proportion ($mcaP_k$), average posterior probability ($avePP_k$), and odds of correct classification (OCC_k). Particularly, classification can be considered good when the $mcaP_k$ for each profile is included in the 95% CI of the π_k, $avePP_k$ values are equal to .70 or higher, and OCC_k values are above 5 (Masyn, 2013; Sorgente et al., 2019).

3.3.2 Association between profiles and socially responsible investing

After identifying the best solution for LPA, the factor scores of the categorical latent variable were saved, to have an observed variable indicating participants' membership to a specific latent profile. This observed variable was investigated in relation to socially responsible investing (not investing in SRI/currently investing in SRI), through a chi-square

Table 1.

Descriptive statistics and correlations between variables included in the LPA

Variable	M	SD	1	2	3	4	5	6	7	8
1. Perceived consumer effectiveness	4.74	1.53	1							
2. Trust	4.47	1.64	.539**	1						
3. Personal norms	5.08	1.23	.574**	.423**	1					
4. Perceived behavioral control	5.36	1.29	.554**	.352**	.691**	1				
5. Financial literacy	2.25	1.35	.121**	-0.034	.071*	.130**	1			
6. SRI knowledge	3.55	1.76	.379**	.415**	.298**	.122**	.012	1		
7. Financial risk tolerance	3.46	1.73	.341**	.416**	.229**	.080*	-0.200**	.527**	1	
8. Environmental concern	5.49	1.29	.472**	.281**	.598**	.728**	.127**	.029	-0.003	1
9. Connectedness to nature	4.85	1.59	.289**	.183**	.444**	.335**	.077*	.188**	.076*	.274**

Note. M = Mean; SD = Standard Deviation; * p <.01, ** p <.001.

test in SPSS (version 27). As suggested by Sharpe (2015), standardized residuals were adopted to interpret chi-square test results, considering that the larger the residual, the greater the contribution of the cell to the magnitude of the resulting chi-square obtained value.

Finally, a univariate analysis of variance (ANOVA) was performed to verify whether the latent profile membership affects the willingness to invest in socially responsible investment products. Post-hoc analyses were implemented using the Tukey's HSD (Honestly Significant Difference) test.

4. Results

Descriptive statistics and correlations for the measures included in the theoretical model are presented in Table 1. As a first step, normality and multicollinearity of the data were checked. Skewness (values between -0.850 and .144) and Kurtosis (values between – 1.150 and .631) were below the suggested cut-offs. According to the Variance inflation factor values (ranging from 1.11 to 2.86), There are also no multicollinearity issues in the data.

4.1 Confirmatory Factor Analysis

The CFA revealed good fit indices for each psychometric scale tested, thus suggesting a highly validity and reliability of the theoretical structure of the measures. Table 2 summarizes fit indices of the CFA performed for the psychometric scales, while standardized factor loadings and Composite Reliability scores are presented in Table 3.

4.2 Latent Profile Analysis

Eight different models of LPA (from 1-class to 8-class) were estimated. We did not proceed with the 9-class model because both the 7- and 8-class solution presented one class with less than 5% of members (respectively 21 and 27 participants). As shown in Table 4, both the 5-class and the 6-class solution satisfied some fit indices. In particular, the inferential indices (the VLMR-LRT and the adjusted LMR-LRT) suggest that the 5-class solution should

Table 2.

Fit indices of the Confirmatory Factor Analysis (CFA)

	χ^2	*df*	p	RMSEA (90% CI)	CFI	SRMR
Perceived consumer effectiveness	.078	2	.003	.000 (.000, .000)	1.000	.001
Personal norms	22.359	9	.008	.038 (.019, .059)	.990	.017
Perceived behavioral control	7.980	2	.019	.055 (.019, .097)	.991	.015
Financial risk tolerance	26.245	5	<.001	.065 (.042, .091)	.984	.018
Environmental concern	30.495	9	<.001	.049 (.030, .068)	.983	.022

Note. χ^2 = chi-square; *df* = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residuals.

Table 3.

Descriptive statistics, standardized factor loadings, and reliability scores for the psychometric scales

Variable	M (SD)	Loading	CR
Perceived consumer effectiveness			.912
1. Investendo in prodotti di investimento sostenibili, ogni investitore può avere un effetto positivo sull'ambiente	4.77 (1.72)	.835***	
2. Investire in imprese attente alla loro responsabilità sociale e ambientale è un modo per avere un impatto positivo sulla società e sul Pianeta	4.76 (1.70)	.862***	
3. Credo che gli investimenti sostenibili possano contribuire alla lotta contro il cambiamento climatico	4.67 (1.76)	.861***	
4. Investendo in aziende che adottano pratiche etiche e sostenibili si può ridurre l'impatto sull'ambiente	4.75 (1.71)	.842***	
Personal norms			.903
1. È importante per me usare prodotti che non causino danni all'ambiente	5.25 (1.42)	.796***	
2. Quando prendo decisioni pongo attenzione all'impatto che queste possono avere sull'ambiente	5.07 (1.52)	.822***	
3. Le mie abitudini d'acquisto sono influenzate dalla mia preoccupazione per l'ambiente	4.79 (1.59)	.792***	
4. Sono preoccupato di sprecare le risorse a disposizione del Pianeta	5.22 (1.54)	.740***	
5. Mi descriverei come una persona responsabile verso l'ambiente	5.25 (1.43)	.743***	
6. Sono disposto a rinunciare alla comodità per adottare comportamenti più rispettosi verso l'ambiente	4.91 (1.51)	.788***	
Perceived behavioral control			.874
1. Penso che con le mie azioni e comportamenti io possa dare un contributo per affrontare il cambiamento climatico	5.23 (1.55)	.807***	
2. Penso che adottando comportamenti più sostenibili potremmo avere un impatto positivo sull'ambiente	5.48 (1.47)	.779***	

2. Penso che adottando comportamenti più sostenibili potremmo avere un impatto positivo sull'ambiente	5.48 (1.47)	.779***	
3. Penso che se ognuno facesse la sua parte potremmo affrontare i problemi associati al cambiamento climatico	5.44 (1.53)	.786***	
4. Penso che le mie azioni possano avere un impatto sull'ambiente	5.29 (1.52)	.814***	
Financial risk tolerance			.919
1. Sono disposto ad assumermi il rischio di perdere denaro a fronte della possibilità di guadagnarne	3.55 (1.99)	.851***	
2. Quando si tratta di investimenti finanziari, sono disposto ad assumermi dei rischi per cercare di ottenere rendimenti più alti	3.51 (1.97)	.840***	
3. Sono sempre più convinto che dovrei assumermi maggiori rischi finanziari per migliorare la mia situazione finanziaria	3.54 (1.97)	.853***	
4. Se penso che un investimento possa essere redditizio, sono disposto a chiedere un prestito per fare questo investimento	3.28 (2.05)	.775***	
5. Penso che sia più importante assumersi dei rischi per avere la possibilità di ottenere rendimenti più alti, piuttosto che fare investimenti prudenti con ritorni garantiti	3.41 (1.96)	.845***	
Environmental concern			.911
1. L'uomo sta abusando gravemente dell'ambiente	5.76 (1.46)	.773***	
2. Il cambiamento climatico sta spingendo il pianeta verso un punto di non ritorno	5.44 (1.58)	.801***	
3. Se le cose continuano così, presto andremo incontro ad una grande catastrofe ecologica	5.42 (1.57)	.841***	
4. La Terra ha spazio e risorse molto limitate	5.29 (1.62)	.687***	
5. Il cambiamento climatico sta alterando l'ambiente in cui viviamo	5.56 (1.58)	.833***	
6. Le risorse naturali del pianeta si stanno consumando irrimediabilmente	5.46 (1.53)	.833***	

Note. M = Mean; SD = Standard Deviation; Loading = Standardized factor loading; CR = Composite Reliability; ***$p < .001$.

be preferred as it explains significantly more ($p < .001$) than solutions with less classes, while being equally good as solutions with more profiles (e.g., $p = .39$ for the 6-class solution). The descriptive indices, instead, do not offer a clear solution. They tend to decrease while the number of classes increases; the only exception is the AWE, for which the lowest value has been found for the 6-class solution. Considering that inferential indices suggest that the 6-class model is as good as the 5-class model ($p = .39$), we preferred the 5-class model according to parsimony criterion. Consequently, the 5-class solution was investigated through classification diagnostics. As reported in Table 5, this solution satisfied all the classification–diagnostic criteria so we proceeded with the interpretation of the classes.

The five obtained classes (see Figure 1), representing different patterns of determinants of SRI decision making, were named as follows. The first profile ($n = 80$; 7.9%) was named “lack of determinants” as it represents the only pattern in which all the nine investment decision determinants (financial literacy, perceived knowledge on SRI, financial risk tolerance, perceived consumer effectiveness, trust, personal norms, perceived behavioral control, environmental concern, connectedness to nature) are lower than the sample average. The second profile ($n = 265$; 26.5%) was named “classic determinants” because the only two indicators for which members of this group were above the sample average were perceived knowledge of SRI and financial risk tolerance. The third profile ($n = 248$; 24.7%) was named “concerned but skeptical of SRI” as it was the only indicator for which participants included in this group were clearly above the sample average. The last two profiles, instead, were composed by participants who reported high levels for most of the determinants of SRI investment decision making. The most relevant difference is that members of profile 4 ($n = 182$; 18.2%) have a very low level of risk tolerance and an almost average level of SRI knowledge. They were indeed named “equipped but risk avoidant”. Members of profile 5 ($n = 227$; 22.7%) had a very high level of risk tolerance, accompanied by high levels of all the

Table 4.

Relative fit indices for LPA measurement models

Model	VLMR-LRT	LMR-LRT	AIC	CAIC	AWE	BIC	SABIC
1-profile	/	/	2,5130.70	2,5237.08	2,5397.46	2,5219.08	2,5161.91
2-profile	$p <.001$	$p <.001$	2,3601.92	2,3767.39	2,4016.87	2,3739.39	2,3650.47
3-profile	$p = .005$	$p = .005$	2,2916.39	2,3140.96	2,3479.54	2,3102.96	2,2982.27
4-profile	$p = .032$	$p =.033$	2,2311.98	2,2595.65	2,3023.32	2,2547.65	2,2395.19
5-profile	$p <.001$	$p <.001$	2,1946.44	2,2289.21	2,2805.97	2,2231.21	2,2046.99
6-profile	$p = .386$	$p = .389$	2,1768.62	2,2170.48	2,2776.35	2,2102.48	2,1886.51
7-profile	$p = .267$	$p = .269$	2,1637.50	2,1559.50	2,2793.43	2,2020.46	2,1772.73
8-profile	$p = .253$	$p = .255$	2,1495.95	2,1407.95	2,2800.07	2,1928.01	2,1648.52

Note. VLMR-LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; LMR-LRT = adjusted Lo-Mendell-Rubin likelihood ratio test; AIC = Akaike information criterion; CAIC = Consistent AIC; AWE = Approximate Weight of Evidence Criterion; BIC = Bayesian Information Criterion; SABIC = sample-size adjusted BIC.

Table 5.

Classification diagnostics for the 5-profile model

Class (N)	CP	95% CI	mcaP	AvePP	OCC
Profile 1 (n = 80)	.078	(.057 .099)	.079	.951	229.41
Profile 2 (n = 265)	.266	(.225 .304)	.265	.912	28.60
Profile 3 (n = 248)	.244	(.186 .299)	.248	.878	22.30
Profile 4 (n = 182)	.188	(.137 .247)	.182	.895	36.82
Profile 5 (n = 227)	.223	(.187 .266)	.227	.916	38.00

Note. CP= class proportion; CI = confidence interval; mcaP= modal class assignment proportion; AvePP = average posterior probability; OCC= odd of correct classification.

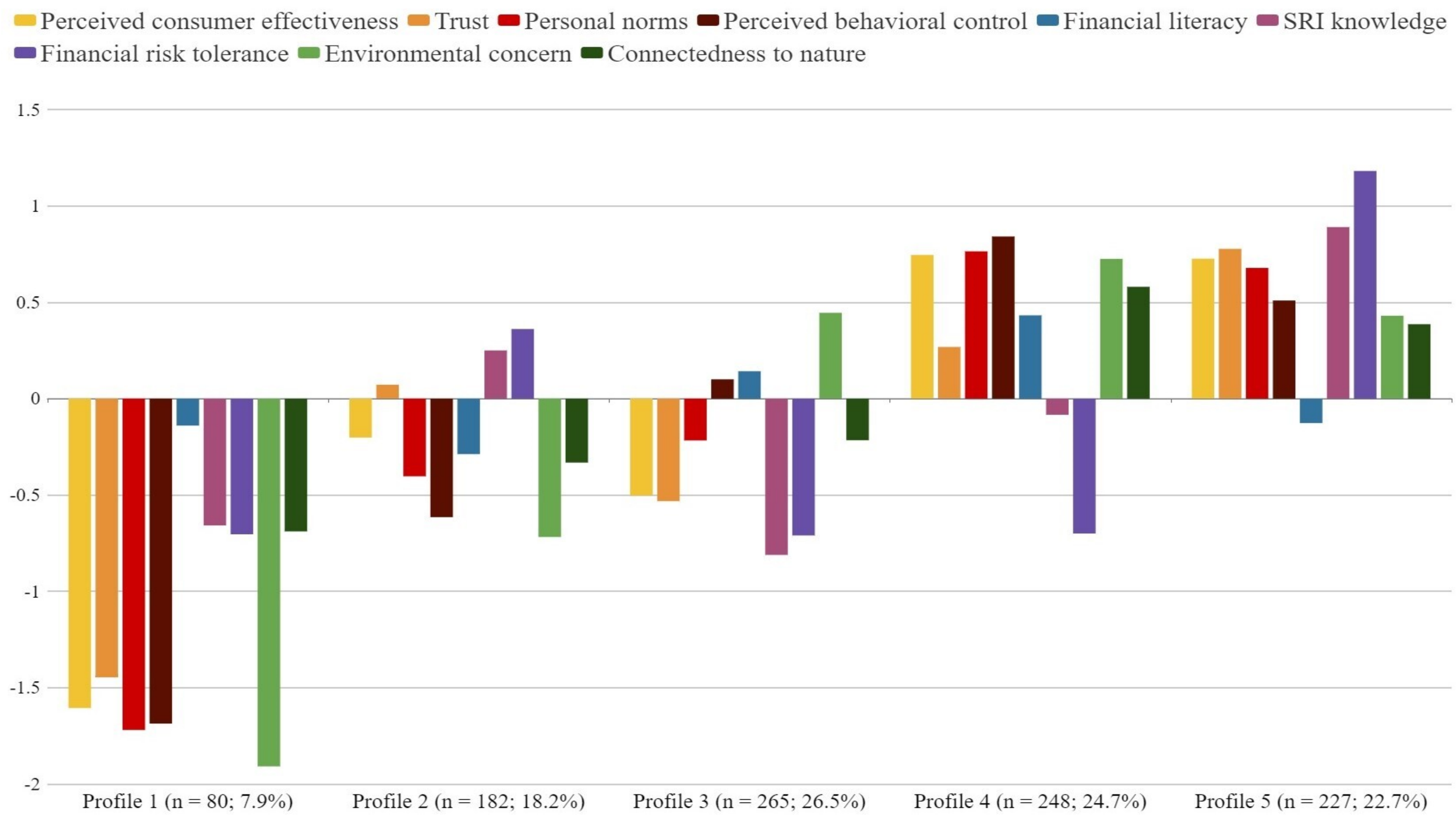

Figure 1.

Representation of the five profiles detected in a sample of 1,002 Italian consumers. Values on the ordinate axis correspond to the factor scores mean level for the nine determinants of sustainable investment decision making.

other determinants and an almost average level of financial literacy. They were indeed named "fully equipped". Socio-demographic characteristics of the five sub-groups emerged through the LPA are reported in appendices (see Table A.1).

4.3 Association between profiles and socially responsible investing

Since the LPA solution showed sufficient levels of Entropy ($E_k > .80$), the factor scores of the obtained latent variable were saved to get an observed measure describing consumers' membership to the five profiles. This variable was then used to identify current and potential socially responsible investors. As for those currently investing in sustainable investment products, we found that the profiles were significantly associated with socially responsible investing [$\chi^2(4) = 41.929$; $p < .001$; Cramer's $V = .205$]. Specifically, as shown in Table 6, consumers belonging to the "fully equipped group" (Profile 5) were more likely to be socially responsible investors than would be expected by chance. In detail, 11.9% of this profile was currently investing in SRI, while the number of SR investors accounted for 4.7% of the total sample. On the contrary, individuals belonging to the "concerned but skeptical of SRI" group (Profile 3) were less likely to be socially responsible investors than would be expected by chance. This sub-sample did not include any socially responsible investor. Profile 2 and profile 4 reported a percentage of SR investors almost like the whole sample (4.7%), respectively 3.4% and 5.5%.

The results from the univariate ANOVA reported differences among profiles in the likelihood of investing in socially responsible financial products. We found that the five latent profiles were significantly associated with the intention to invest in SRI in the next six months [$F(4, 997) = 107.523$; $p < .001$; partial $\eta^2 = 0.301$]. The partial eta squared (η^2) indicated a large effect size. Furthermore, post-hoc analyses showed that all the five subgroups were significantly different from each other. The highest likelihood of socially responsible investing was reported respectively by the "the fully equipped" group (Profile 5; $M = 5.32$;

Table 6.

Cross-tabulation of personality profiles and socially responsible investing

	Observed values (adjusted residuals)			
	Willingness to invest in SRI	SR investors	Not SR investors	Total
Profile 1 (lack of determinants)	$M = 2.39$; $SD = 1.45$	1 (-1.5)	79 (1.5)	80
Profile 2 (classic determinants)	$M = 4.02$; $SD = 1.27$	9 (-1.2)	256 (1.2)	265
Profile 3 (concerned but skeptical of SRI)	$M = 3.03$; $SD = 1.53$	0 (**-4.0**)	248 (**4.0**)	248
Profile 4 (equipped but risk avoidant)	$M = 4.65$; $SD = 1.73$	10 (.6)	172 (-.6)	182
Profile 5 (fully equipped)	$M = 5.32$; $SD = 1.33$	27 (**5.8**)	200 (**-5.8**)	227
Total	$M = 4.05$; $SD = 1.74$	47	955	1,002

Note. Adjusted residuals in bold are those that exceed +/- 2 as suggested by Sharpe (2015)

SD = 1.33) and those “equipped but risk avoidant” (Profile 4; M = 4.65; SD = 1.73). On the contrary, the lowest score of intention towards SRI was shown by members of the “concerned but skeptical of SRI” group (Profile 3; M = 3.03; SD = 1.53). The scores of “classic determinants” group (Profile 2; M = 4.02; SD = 1.27) were quite like the sample mean (M = 4.05; SD = 1.74).

5. Discussion

The purpose of the present study was to identify the characteristics of socially responsible investors. Using cross-sectional data of a representative sample of Italian consumers, a LPA was performed to identify different subgroups of respondents, characterized by different configuration of determinants of sustainable investment decision making. The association between the profiles emerged from our sample and the (current and potential) decision to invest in sustainable investment products was subsequently tested through Chi-square test and ANOVA. The LPA resulted in five different profiles, though only one of them, “the fully equipped” ones (Profile 5) was significantly more likely to include socially responsible investors. On the contrary, the “concerned but skeptical

of SRI” group (Profile 3) was composed of consumers less likely to invest in socially responsible financial products. As for potential investors, the findings were quite similar, since “the fully equipped” profile (Profile 5) reported the highest willingness towards socially responsible investing, followed by the “equipped but risk avoidant” group (Profile 4). As well, profile 3 (i.e., the “concerned but skeptical of SRI” ones) reported the lowest scores in the intention to invest in sustainable financial products.

Our results suggested that socially responsible investing is a matter of different aspects. As shown by the “classical determinants” group (Profile 2), classical determinants of investment decision making (i.e., risk tolerance and SRI knowledge) are not enough to explain the decision to invest responsibly. Furthermore, this profile reported lower levels than the average for environmental concern, and perceived behavioral control over the environment. Environmental concern alone was irrelevant as well. Indeed, the group "concerned but skeptical of SRI" (Profile 3) was significantly less likely to include current or potential investors. It should be considered that this group was both lacking classical antecedents of investment decision making and showing negative attitudes (i.e., low levels of trust and perceived consumer effectiveness) towards SRI.

The "equipped but risk avoidant" and "fully equipped" groups (respectively, Profile 4 and 5) manifested many similarities, as they both reported positive attitudes towards SRI, together with higher levels of perceived behavioral control, environmental concern, and connectedness to nature. However, the two subgroups had also some differences. Indeed, those in the "equipped but risk avoidant" profile reported scores of financial literacy above the average, knowledge on SRI was close to the mean level and risk tolerance was significantly below the mean scores. Furthermore, this group did not manifest levels of trust towards SRI as high as the "fully equipped ones". Conversely, the "fully equipped" ones were characterized by levels of financial literacy slightly below the average. The trend of the two groups would suggest that objective financial literacy is less relevant in the decision to invest in SRI. Various explanations can be drawn. Maybe, general knowledge is less determinant than specific knowledge on SRI. It should be also considered that knowledge on SRI was measured through a self-report item. On fact, it was a measure of perceived knowledge, rather than objective knowledge. Literature suggested a great gap between actual and self-assessed financial knowledge. Furthermore, it seems that in financial behaviors and decisions, perceived competencies might play a greater role than effective skills and knowledge themselves (Allgood & Walstad, 2016). This evidence could explain the pattern of the "fully equipped" group. Knowledge on SRI and risk appetite seem to have a key role in shaping actual sustainable investment decisions. We speculate that the reason why members of the "equipped but risk avoidant" group showed only intentions towards SRI, rather than actual investment decisions, is rooted in their lack of adequate levels of knowledge and risk appetite. Furthermore, differences between the two profiles make us suggest that environmental concern, connectedness to nature, personal norms, positive attitudes towards SRI and perceived control over the environment affect the decision to invest responsibly. At the same time, the role of classical antecedents of investment decision making should not be overlooked. Socially responsible investing is a matter of both psychological characteristics and classical antecedents of investment decisions, such as knowledge and risk appetite. In this direction, the "equipped but risk avoidant" ones might experience the so-called intention-behavior gap due to a lack of essential determinants in investment decision, in particular risk appetite.

The findings reported in the present study highlight the strengths of adopting a person-centered approach, as it allows us to estimate the effect of different configurations of the same variables on an outcome. Specifically, in the present study, socially responsible investing resulted to be shaped by a joint effect of both classical determinants of investment decisions, and non-financial aspects, such as moral values and consumers' attitudes. Our results are generally consistent with previous studies, showing that the profiles of socially responsible investors are characterized by a mixture of higher knowledge on SRI, risk appetite, positive attitudes towards SRI, personal values, perceived control over the environment, awareness on environmental issues and connectedness to nature (e.g., Apostolakis et al., 2018b; Gutsche & Zwergel, 2020; Gutsche et al., 2021; Roos et al., 2022). The profiles of potential sustainable investors are quite similar, though a subgroup of potential investors (Profile 4) reported perceived knowledge about SRI slightly below the average and a financial risk tolerance below the sample mean. We suggest that the reason why this profile includes only potential investors is rooted in the lack of relevant determinants in investment decision making (e.g., risk appetite). However, these results are in line with previous studies, which reported mixed results for the role of financial skills and risk appetite in socially responsible investing (Delsen & Lehr, 2019; Rossi et al., 2019). This matter deserves further investigation in future.

The present study is not lacking limitations. The first limit refers to the use of cross-sectional data. Since surveys rely on self-report items, data might also be somehow influenced by social desirability or other response biases. Furthermore, seen the exploratory nature of our contribution and the inclusion of Italian respondents, every kind of causal relationship and generalizability outside the Italian context should be made cautiously. Finally, despite the great number of variables included in our conceptual model, investors' motivations behind socially responsible investing were not attentioned. Nilsson (2009) suggested that people could invest in SRI for various reasons. While some may be attracted by the idea of investing in agreement with their personal values, others could conceive SRI as a way to diversify their portfolio or obtain better financial performance. Future studies should include this issue as well and better explore this topic.

CHAPTER 4

USING MACHINE LEARNING ALGORTIHMS TO VALIDATE THE LATENT PROFILE SOLUTION

The present study aimed at validating the theoretical model presented in Chapter 3. Indeed, as suggested by Sinha et al. (2021, p. 77), "A key component to demonstrating the validity of classes or subgroups identified using algorithms such as LCA is to demonstrate their reproducibility". The reproducibility of the obtained solution is classically tested using external dataset with new cases, or by splitting the dataset in sub-samples (Masyn, 2013). It is suggested then to verify whether the solutions emerged from the two datasets reported the same number of clusters and if the characteristics of the profiles have a similar data pattern (Sinha et al., 2021).

For research purposes, a novel technique involving machine learning algorithms was developed to validate the model. Specifically, relying on the solution provided by the LPA presented in Chapter 2, predictive algorithms were trained to classify individuals in the five profiles. The group membership of the sample was used as label for the training phase of algorithms. In other words, classification algorithms were trained to assign the profile membership based on the provided labels, and test if they are capable of correctly classifying individuals in the profile suggested by the LPA. Since this step usually requires the training of different algorithms, to find those that work best with available data, four different machine learning algorithms were tested (i.e., Artificial Neural Networks, Random Forest, Gradient Boosting, and Support Vector Machines).

The chapter is structured as follows. Section 1 provides a detailed theoretical background. Section 2 includes the description of the procedure adopted for training and testing the machine learning techniques. Once theoretical aspects are discussed, the analytic plan is detailed in Section 3, while the results for the predictive capability of the model are provided in Section 4. Finally, Section 5 reports the discussion and conclusive remarks of the study, while limitations are outlined in Section 6.

1. Theoretical background

1.1 Explanatory Modelling and Predictive Modelling

Analysing data and drawing conclusions from it requires researchers to make various choices regarding the background theoretical model, the analytical techniques employed, and the evaluation of the tested model. The term used to encompass all these steps is “statistical modelling”. Breiman (2001) argues that there are two cultures in the application of statistical modelling: one, known as “explanatory modelling” or "data modelling culture", adheres to an explanation-oriented approach to science; the other, known as “predictive modelling” or “algorithmic modelling culture”, follows a prediction-oriented approach.

As reported by Shmueli (2011), the process leading to explanatory analysis is typically as follows: research hypotheses are defined based on theoretical constructs, and, usually, there is a diagram illustrating the causal relationships between the constructs hypothesized by researchers. Subsequently, a connection is made between the construct and directly observable measurements using theoretical justifications and relying on the reference literature: the construct is operationalized. After these steps, the statistical model used and its assumptions are introduced: explanatory modelling requires interpretable statistical models linked to the underlying theoretical model, and the main objective is to reproduce the model parameters using statistical inference. Model validation involves a series of inferential decisions aimed at critically discussing the result obtained in the estimation phase: in this phase, various aspects of the estimated model are examined to evaluate its goodness of fit to the data and its explanatory capacity.

The term "predictive modelling" refers to the process that, through the application of statistical models or data mining algorithms to data, allows predicting new or future observations. A predictive model is any model that allows prediction, regardless of its approach: Bayesian, frequentist, parametric, non-parametric, using data mining algorithms, or statistical models (Breiman, 2001; Shmueli, 2011). In this approach, it is not necessary to know the exact role of each variable in terms of the underlying causal structure: the criteria for choosing variables reside in the quality of the association between predictor and response and in the data quality. In this case, it is the data that drive the process and not the underlying theoretical formulation. In the context of predictive modelling, validation focuses on generalization, that is the model's ability to accurately predict new observations. What could affect the generalization capacity is the overfitting, that is the over-adaptation of the model to the data used to build it. The validation of predictive models includes techniques to evaluate the predictive accuracy of the model and the degree of overfitting, usually by comparing the model's performance on the data used to build it and on new data, or by using cross-validation techniques.

Despite the growing popularity of predictive techniques in psychology and social sciences, statistical modelling for explanation remains the predominant approach. Conversely, in domains such as bioinformatics and natural language processing, algorithmic modelling predominates (Breiman, 2001; Yarkoni & Westfall, 2017). However, integrating a predictive perspective into social sciences opens the possibility of exploring analysis tools commonly employed in other scientific fields where the predictive approach is prevalent, such as numerous Machine Learning algorithms. The adoption of predictive methods implies embracing their associated procedures for model construction and evaluation, ultimately resulting in models with higher predictive accuracy. Moreover, predictive techniques can serve as a means to overcome the assumptions of explanatory models, including the assumption of linear relationships between variables.

In conclusion, the combined use of explanatory methods and predictive techniques, along with comprehensive model evaluation, including both in-sample and out-of-sample measures, could lead to the development of models and measurement tools with sufficient predictive capacity. This approach preserves an explanatory foundation, enabling theoretical interpretation and offering insights into the predictive validity of the model (Hofman et al., 2021; Rocca & Yarkoni, 2021).

1.2 Machine Learning Techniques for Predictive Modelling

Machine Learning (ML) is a fundamental branch of Artificial Intelligence that focuses on developing algorithms and models capable of learning from data and making predictions or decisions without being explicitly programmed. In the context of ML, a common distinction is between supervised and unsupervised learning.

Unsupervised learning deals with unlabelled data, where the model identifies patterns or structures without explicit guidance. Unsupervised learning techniques include clustering, dimensionality reduction, and anomaly detection. It has applications in customer segmentation, data exploration, and recommendation systems (e.g., Chiu et al., 2021). Supervised learning involves training models using labelled data. The model learns from input-output pairs, mapping input data to corresponding output labels. This approach enables predictions or classifications for new, unseen data. It finds applications in tasks like spam detection, sentiment analysis, and medical diagnosis (e.g., Mehta et al., 2020; Renuka et al., 2011). If we consider the approach proposed in this chapter, we are moving in the context of supervised learning. Indeed, our goal is to build a model that can learn from some examples and accurately predict the answers for new inputs it has never seen before.

In supervised learning, we encounter two main types of problems: regression and classification. In regression the aim is to predict a numerical continuous value. In classification, the goal is to predict a *class label*, which is a choice from a predefined list of possibilities. Classification is sometimes separated into *binary classification*, which is the special case of distinguishing between exactly two classes, and *multiclass classification*, which is classification among more than two classes. This last problem is the problem of interest of this study.

2. Data analysis

The approach adopted in this study can be divided into two sequential steps. The first one refers to the identification of the sub-groups within the sample, while the latter regards the training of classification algorithms to assign new cases to the latent sub-groups previously found. 802 cases (80%) were randomly extracted out of the total sample of 1,002 individuals for research purposes. Then, a Latent Profile Analysis (LPA) was performed on the sub-sample of 802 individuals. The nine measures (i.e., perceived consumer effectiveness, trust, personal norms, perceived behavioral control, financial literacy, SRI knowledge, financial risk tolerance, environmental concern, and connectedness to nature), previously discussed in Chapter 2, were used as indicators in the LPA to find sub-groups within the sub-sample. Analyses were executed in Mplus (v. 8.7).

Subsequently, four classification algorithms (i.e., Support Vector Machines, Artificial Neural Networks, Random Forest, and XGBoost) were trained to correctly predict the group membership of these participants based on the segmentation suggested by the LPA as the label. The second sub-sample (n = 200; 20%) was then considered for robustness check, in order to verify the reliability of our findings. Precisely, besides training and testing the algorithms on the same data used to perform the LPA, we also wanted to check the classification accuracy by providing unseen cases to assign across the profiles found in the first phase. In other words, the reproducibility of the solution was also evaluated by predicting the cluster assignment of out-of-sample cases that were not included in the previous analyses.

3. Training and Evaluating Classification Algorithms

Relying on a label representing the cluster membership of each respondent, various classification algorithms can be trained to predict the group membership of new cases. The main purpose is to compare the predictive accuracy of these algorithms and select the best-performing one. Following the training phase, the classification algorithm then becomes capable of assigning individuals who have not been encountered before (i.e., out-of-sample data) to a latent profile basing on input data, such as item responses or factor scores. Over the years, various ML algorithms have been proposed for solving classification problems (Kotsiantis et al., 2006). For research purpose, we tested the performance of four of the most used classification algorithms: Support Vector Machines, Artificial Neural Networks, Random Forests, and XGBoost (or Gradient Boosting).

The procedure for training and testing the different classification algorithms shares common steps. In the initial stage, parameter optimization is crucial. Due to the vast parameter space, a grid search can be performed to explore various parameter combinations, aiming to achieve the highest predictive performance (Yu & Zhu, 2020). Following the parameter search, the subsequent steps involve training and evaluating the algorithms.

In classification problems, a critical challenge during training is the risk of "*overfitting*". Overfitting occurs when a model performs exceptionally well on the data used for training the algorithm (training set) but poorly on the out-of-sample data (test set). The problem of over-fitted model is that it tends to memorize all data, including noise present in the training set, instead of learning the underlying patterns. Overfitting is more likely to occur when the training set is small, lacks representative data, or contains excessive noise. In such cases, the algorithm may learn and rely on noise, impacting the accuracy of predictions on out-of-sample data (Ying, 2019). To address this issue, one potential solution is to rely on a family of techniques named "*cross-validation*". While the use of cross-validation may not entirely eliminate or prevent overfitting, it provides a robust estimation of the model's actual performance (Raschka, 2018). One of the most used cross-validation techniques is "*k-fold cross-validation*," where the original sample is randomly divided into *k* sub-samples of equal size. In each iteration, a single sub-sample serves as the test set, while the remaining *k-1* sub-samples act as the training data. This process is repeated *k* times, using each sub-sample as the validation set in each iteration. All observations are utilized for both training and validation, with each observation employed for validation only once. To generate a single estimate, the performance of the *k* iterations is usually averaged. Typically, *k* takes a value ranging from 5 to 10 (Hastie et al., 2009). The cross-validation procedure is depicted in Figure 1.

An alternative to cross-validation for evaluating out-of-sample performance is to maintain the training set and test set as entirely distinct datasets. Typically, a test set comprising 30-50% of the original data is randomly extracted and set aside, while the remaining data is used for model construction (Attewell & Monaghan, 2015). The key feature of this approach is that, since the test set is randomly partitioned from the training set, the only commonality between the two datasets is the data generation process. Consequently, if a model fits well with the test set, it is reasonable to argue that the theoretically grounded model captures the essential elements of the data generation process. If a large dataset is available, cross-validation can be performed on the training set, and the performance can also be assessed on a separate test set.

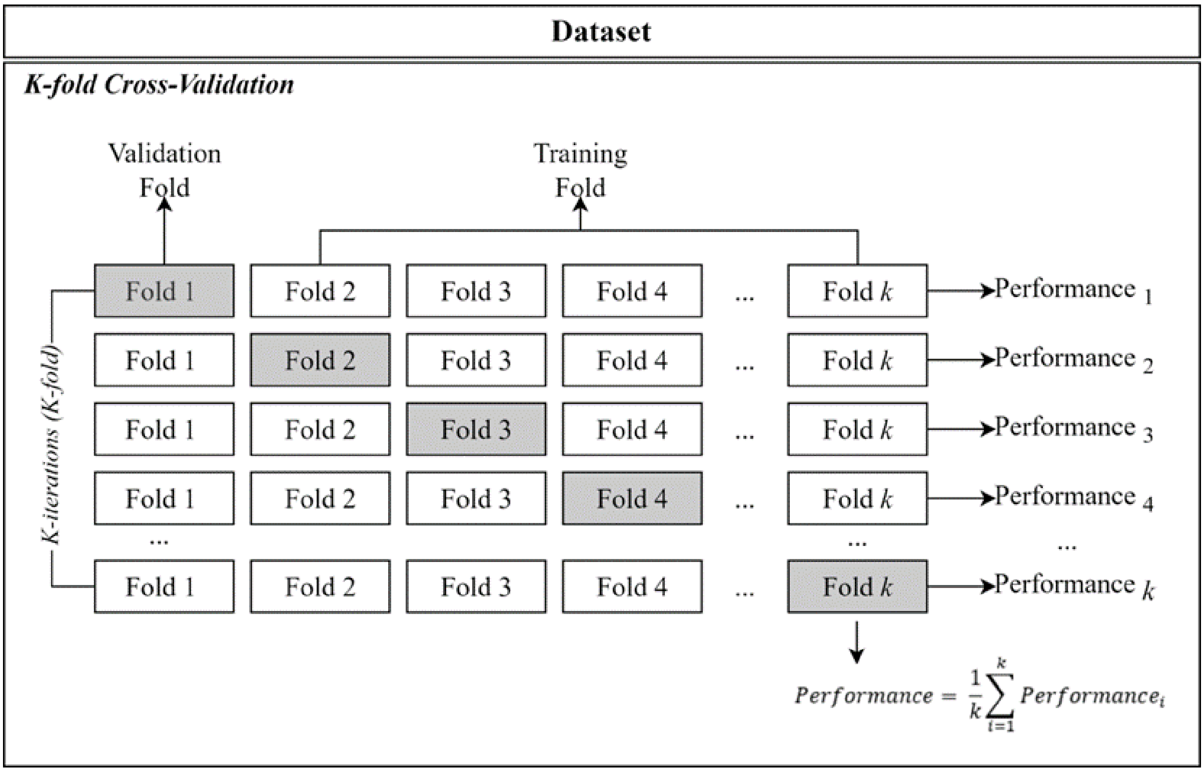

Figure 1.

Representation of the K-fold cross-validation procedure.

To evaluate models in classification problems, predictive accuracy is one of the most commonly reported metrics. Predictive accuracy represents the proportion of correct predictions relative to the total number of predictions made by the model. It serves as a fundamental and easily interpretable measure of a model's overall performance in correctly classifying instances within a given dataset. While predictive accuracy provides a valuable overview of a model's success, it's important to note that in some cases, other metrics like precision, recall, F1 score, and area under the ROC curve may offer a more nuanced understanding, especially when dealing with unbalanced datasets or specific objectives within the classification task.

Table 1.

Descriptive statistics for socio-demographics and measures of the sample

Variable	Total (N = 1,002)	Sub-sample 1 (n = 802)	Sub-sample 2 (n = 200)
Gender:			
Male	50.1%	51.5%	44.5%
Female	49.9%	48.5%	55.5%
Age	37.19 (10.94)	37.27 (10.87)	36.84 (11.19)
Education:			
University degree	31.4%	31.3%	32%
High school degree	52%	51.5%	54%
Middle school degree	16.6%	17.2%	14%
Trust	4.47 (1.64)	4.36 (1.63)	4.92 (1.61)
Perceived consumer effectiveness	4.74 (1.53)	4.68 (1.52)	4.96 (1.58)
Personal norms	5.08 (1.23)	5.04 (1.22)	5.25 (1.27)
Perceived behavioral control	5.36 (1.29)	5.33 (1.27)	5.49 (1.38)
Financial literacy	2.25 (1.35)	2.28 (1.34)	2.15 (1.39)
SRI knowledge	3.55 (1.76)	3.53 (1.74)	3.65 (1.84)
Financial risk tolerance	3.46 (1.73)	3.42 (1.68)	3.61 (1.90)
Environmental concern	5.49 (1.29)	5.45 (1.29)	5.65 (1.28)
Connectedness to nature	4.85 (1.59)	4.84 (1.58)	4.89 (1.65)

Note. Means (Standard Deviations) are reported.

4. Results

4.1 Sub-groups identification

Descriptive statistics for socio-demographics and measures considered within the LPA are summarized in Table 1. Seven LPA models were estimated, starting from 1-profile solution to a 7-profile solution. Since the 7-profile solution showed a group with less than 5% of members (i.e., 3.2% of the sample) we did not proceed estimating a 8-profile model. Table 2 reports fit indices for the seven solutions. Overall, indices suggested the 5-profile solution as the best one. Precisely, according to the inferential indices (i.e., VLMR-LRT and the adjusted LMR-LRT), the 5-profile solution should be preferred as it was significantly more explanatory than the 4-profile model. At the same time, the 6-profile solution did not offer greater explanatory power than the 5-profile solution. Hence, for parsimony criterion we should opt for the solution with less profiles. Instead, most of the descriptive indices were not informative as their value decreased when the number of profiles increased. The AWE was the only exception, showing the lowest value for the 5-profile solution. Hence, the model with five profiles was retained.

Subsequently, the classification quality (i.e., the accuracy of individuals' classification) of the 5-profile solution was tested. First of all, Entropy was above the suggested cut-off of .80 (E_k = .852), indicating a high-quality classification. As reported in Table 3, classification diagnostics were all satisfied, thus suggesting that the 5-profile solution yields well-separated and highly differentiated groups.

After identifying the best solution for the LPA and testing its classification quality, the factor scores of the categorical latent variable were saved, to have an observed variable indicating participants' membership to a specific latent profile (Ferguson et al., 2020). In other words, individuals were modally assigned to the profile with the highest posterior class probability for the individual participant (i.e., the groups they were more likely to belong to).

Table 2.

Relative fit indices for LPA measurement models

Model	VLMR-LRT	LMR-LRT	AIC	CAIC	AWE	BIC	SABIC
1-profile	/	/	1,9953.49	2,0055.49	2,0211.86	2,0037.49	1,9980.33
2-profile	$p < .001$	$p < .001$	1,8779.77	1,8939.01	1,9182.25	1,8911.01	1,8822.09
3-profile	$p = .001$	$p = .001$	1,8269.56	1,8485.67	1,8815.78	1,8447.67	1,8326.99
4-profile	$p = .015$	$p = .016$	1,7778.82	1,8051.79	1,8468.78	1,8003.79	1,7851.37
5-profile	$p < .001$	$p < .001$	1,7496.19	1,7826.05	1,8329.89	1,7768.05	1,7583.86
6-profile	$p = .134$	$p = .138$	1,7389.54	1,7776.26	1,8366.98	1,7708.26	1,7492.32
7-profile	$p = .487$	$p = .492$	1,7283.49	1,7205.49	1,8404.69	1,7649.09	1,7401.39

Note. VLMR-LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; LMR-LRT = adjusted Lo-Mendell-Rubin likelihood ratio test; AIC = Akaike Information Criterion; CAIC = Consistent AIC; AWE = Approximate Weight of Evidence Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-size Adjusted BIC.

Table 3.

Classification diagnostics for the 5-profile model

Profile (N = 802)	CP_k	95% CI	$mcaP_k$	$AvePP_k$	OCC_k
Profile 1 (n = 68; 8.5%)	.084	(.063 .108)	.085	.968	329.87
Profile 2 (n = 217; 27.1%)	.270	(.225 .312)	.271	.910	27.34
Profile 3 (n = 196; 24.4%)	.245	(.184 .307)	.244	.885	23.72
Profile 4 (n = 152; 18.9%)	.188	(.134 .246)	.189	.879	31.38
Profile 5 (n = 169; 21.1%)	.213	(.172 .254)	.211	.924	44.92

Note. CP_k = Class Proportion; CI = Confidence Interval; $mcaP_k$ = modal class assignment Proportion; $AvePP_k$ = Average Posterior Probability; OCC_k = Odds of Correct Classification.

The five profiles are represented in Figure 2. Profile 1 (n = 68; 8.5%) shows levels below the sample average for each indicator considered within the LPA. Individuals in profile 2 (n = 217; 27.1%) are characterized only by higher knowledge on SRI and risk tolerance. They also show levels of personal norms, perceived behavioral control and environmental concerns strongly below the mean scores. Profile 3 (n = 196; 24.4%) reports scores above the mean only for environmental concerns. At the same time, it generally shows negative attitudes towards SRI (i.e., levels for trust and perceived consumer effectiveness below the mean scores), together with low knowledge on sustainable investments and risk appetite. Profile 4 (n = 152; 18.9%) is instead denoted by levels above the sample average for almost every determinant, except for SRI knowledge and financial risk tolerance, which is quite below the mean score. Finally, Profile 5 (n = 169; 21.1%) reports high scores for each variable, except for financial literacy, which is slightly below the mean score.

4.2 Training and evaluation of classification algorithms

Once the clusters within the sample were identified, classification algorithms were then trained to classify individuals in the latent sub-groups. ML algorithms were implemented using the Python programming language with Keras and Scikit-Learn modules. The algorithms were trained on the sub-sample comprising 802 individuals, and their predictive cross-validated accuracy was compared to selecting the best model. All ML algorithms take item responses as input and provide the membership of respondents as output. Grid search was employed to select the parameters for each algorithm, and a five-fold cross-validation was applied for each one. The following section provides a detailed description of each algorithm and its related parameters.

The Support Vector Machines algorithm was configured with a regularization parameter (C) set to 100. This parameter indicates the trade-off between achieving a smooth decision boundary and classifying training points correctly. To control the influence of

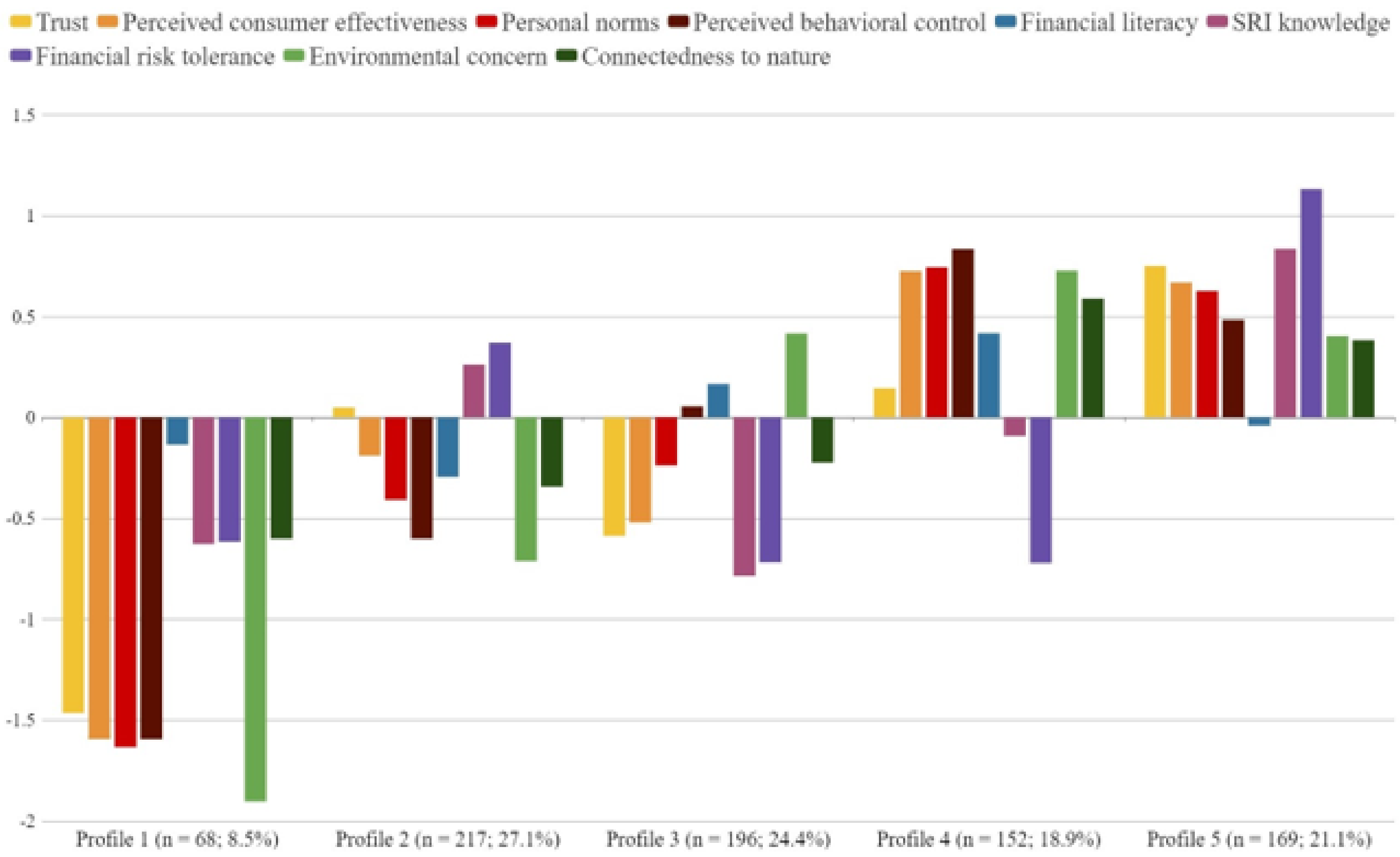

Figure 2.

Representation of the five profiles detected in a sample of 802 Italian consumers individual training samples on the model, a gamma value of .001 was chosen. For this parameter, lower values emphasize a more extended influence. The choice of the Radial Basis Function (RBF) kernel was made to capture complex or non-linear relationships within the data.

The Artificial Neural Network was designed with three layers: the input layer consists of 32 nodes (i.e., the number of items), the hidden layer had 20 neurons with a *tanh* activation function and the output layer had 5 neurons with a *softmax* activation function. The neural network was trained for 250 epochs, utilizing the Adam optimizer with a learning rate set to .01 and a batch size of 16. Categorical cross-entropy was the chosen loss function. One-hot encoding was performed to transform the target (that is the group of the subject) into binary features. The use of the softmax function and one-hot encoding enabled the output of the neural network to represent the probability of each individual belonging to a specific group. Consequently, the group with the highest probability was selected for each respondent.

The Random Forest ensemble was configured with no bootstrap, the maximum depth of each tree (max_depth) was left unrestricted, and the number of features considered for the best split at each node (max_features) was set to the square root of the total number of features. The minimum number of samples required in a leaf node (min_samples_leaf) was set to 2, while the minimum number of samples required to split an internal node (min_samples_split) was set to 3. The ensemble comprised 300 trees.

As for the XGBoost model, the fraction of features randomly sampled when constructing each tree (colsample_bytree) was set at .7, controlling diversity by considering 70% of the features for each tree. A gamma value of .15 was chosen to regulate the tree's complexity and prevent overfitting. The learning rate was set to .3, influencing the convergence speed towards the minimum of the loss function at each iteration. The maximum depth of each tree (maximum_depth) was set at 2 to capture simpler relationships in the data, and the number of boosting rounds (n_estimators) was set at 100. Finally, the fraction of the training data randomly sampled for growing each tree was set to .5.

The learning parameters for all the algorithms are summarized in Appendices (see Table A.2). Table 4 presents the cross-validated predictive accuracy for the training set and the validation set achieved by each algorithm. All algorithms prove satisfactory predictive accuracy, with Support Vector Machines consistently reporting the highest value on the validation set.

Table 4.

Cross-Validated Training and validation accuracies for the tested algorithms

Algorithm	Training Accuracy	Validation Accuracy
Support Vector Machines	99.9%	95.3%
Artificial Neural Networks	96.8%	80.2%
Random Forests	99.6%	72.2%
XGBoost	100%	90%

4.3 Robustness check

At this point, a question may naturally arise. Can we trust the outcomes yielded by these algorithms? Indeed, since they are trained on the same data used for the LPA, it would be easier for them to predict the cluster membership and correctly assign individuals. To dispel this doubt and check the reproducibility of our solution, the predictive accuracy of classification algorithms for unseen cases was also tested. We predicted group membership of the external dataset (n = 200) that was not included in previous analyses. Specifically, the four trained algorithms were used to predict the group membership of this second dataset. The choice to include this data only at this point (i.e., after the training phase) ensures that the ML models are not influenced by the groupings from the second sub-sample. Indeed, these respondents would influence the final solution retrieved by the LPA by contributing to the estimation of the profiles. This approach thus maintains the integrity of the test data and provides a more accurate measure of algorithms predictive capabilities.

To have a measure of the effective predictive accuracy, the solution provided by ML classification algorithms for these unseen cases was then compared to the classification suggested by the LPA performed on the total sample (N = 1,002). Before making this comparison, we ensured that the solutions derived from the two LPAs were nearly equivalent in terms of both number of profiles that emerged and variable patterns (i.e., mean scores for the variables used to identify the sub-groups). In both cases, the best solution suggested by data indicated the existence of 5 latent sub-groups. Furthermore, these profiles obtained from the total sample (N = 1,002) and the first sub-sample (n = 802) showed almost the same data patterns, in terms of indicator configurations. In other words, as shown in Appendices (see Tables A.3), the mean scores of these indicators for the five profiles were quite similar across the two LPAs. Finally, to further ensure the equivalence of solutions, we also tested whether the profiles assigned to the 802 individuals present in both datasets were the same for the two LPAs. In 98.38% of cases (n = 789), individuals were assigned to the same profiles. These findings suggest that the two solutions were almost identical.

Subsequently, the predictive capability of the four trained ML models was tested on this second sub-sample (n = 200). To obtain an accuracy score, classifications suggested by algorithms were compared with the group assignment provided by the second LPA. For each algorithm, an index representing the convergence between the two solutions was calculated. Accuracy values were high in predicting group assignment also for new individuals (Random Forest accuracy = 75.3%; Artificial Neural Networks = 84.4%; XGBoost accuracy = 87.5%; Support Vector Machine accuracy = 90%).

5. Discussion

Overall, our findings suggest that ML algorithms function as robust tools in predicting group membership, thus suggesting a good reproducibility of the obtained solution. Indeed, the four trained algorithms reported good validation accuracy. It is important to highlight that we conducted a rigorous evaluation by testing the trained algorithms on data not used in the LPA model estimation (i.e., robustness check), ensuring a more comprehensive assessment of their accuracy. The classification algorithms were also able to correctly classify unseen cases, as tested to verify the robustness of our solutions. Such findings further confirm the validity and reproducibility of the model developed in Chapter 3.

The limitation of this study, and more generally of the approach adopted, relies on the assumptions and limitations of the employed methods. First, the way in which the ML algorithm assigns the group membership depends entirely on the LPA solution: so, we are assuming that the solution of LPA is effective in retrieving latent profiles that naturally exist in our sample. Furthermore, adequate sample size and representativeness are essential for reliable LPA model estimation and ML algorithm training. Unbalanced or non-representative data may introduce bias and uncertainty in cluster assignments, impacting the overall validity of the results. The characteristics of the data significantly influence the selection of the most suitable algorithm. In this study, Support Vector Machines demonstrates the highest predictive accuracy; however, this outcome should not be regarded as absolute. The performance of algorithms is contingent upon the specific characteristics of both the task and the input data.

CHAPTER 5

NUDGING SOCIALLY RESPONSIBLE INVESTMENTS

The last chapter of this doctoral thesis presents an experimental study aimed at testing the effect of behavioral change interventions in shaping socially responsible investing. For research purposes, two different kinds of nudges were developed and tested in a simulated investment scenario. Specifically, a website for a fictitious bank was created. Within the website, six different investment portfolios were proposed. Participants were randomly split between a control condition and the two experimental conditions. The task simply required making investment decisions by considering the information provided for each portfolio. The available information in the scenario concerned risk, annual performance, and ESG score for the six investment alternatives. Each of the three conditions differed from the others in the way such information was provided. In other words, the website page was slightly different across conditions in terms of choice architecture, to assess the effectiveness of the two nudges in promoting SRI among Italian consumers.

The chapter is organized as follows. The first section includes a review of the literature, first focusing on nudge theory and then summarizing the adoption of these behavioral change interventions in the context of SRI. Section 2 describes the experimental rationale in detail. The methodology is then reported in Section 3. Finally, the results obtained are described in Section 4 and discussed in Section 5.

1. Theoretical framework

1.1 Nudges and the choice architecture

Within behavioral economics framework, we can identify two distinct approaches that examine the concept of bounded rationality (Altman, 2012). The first perspective follows the work of Kahneman and Tversky, who highlighted the clear limits of human rationality (see Kahneman & Tversky, 1979; Tversky & Kahneman, 1974). The two authors argue that people often make systematic errors in the decision-making process. These errors occur when individuals deviate from analytical reasoning and rely on emotional cues or cognitive shortcuts (i.e., heuristic strategies). Accordingly, human thinking would be inherently flawed due to the tendency to use heuristics - conceived as systematic violations of the rational decision-making processes - which lead to cognitive fallacies (Hertwig & Grune-Yanoff, 2017).

The second approach asserts instead that reality is too complex for humans to fully grasp. As a result, heuristic strategies have been developed over time to cope with the limits of human cognition and the lack of sufficient information in the environment (Altman, 2012). Gigerenzer (2007) refers to this as "ecological rationality," emphasizing humans' ability to adapt effectively to different environments and contexts over time. While this perspective also recognizes the limitations of human cognition, it suggests that cognitive and motivational processes can be improved. For instance, by teaching people new thinking and reasoning strategies or helping them understand which mental processes are most suitable for specific situations (Hertwig & Grune-Yanoff, 2017).

The theory of nudges is rooted in Kahneman and Tversky's concept of bounded rationality, which posits that human thought is so constrained by limitations and biases that external interventions are justified in shaping individuals' choices and actions. According to Kahneman (2011), the human mind can be metaphorically divided into two systems: the first is intuitive, fast, and prone to systematic biases, while the second is analytic, slow and deliberative. Behavioral change can thus be pursued through two different approaches: the first exploits the fallacies of the intuitive system, while the second involves interventions aimed at enhancing the slower system to compensate for the limitations of the faster one. The main challenge with the latter option is that cognitive and motivational deficits are particularly difficult to improve. Hence, for the author, it may be more effective to follow the first path, focusing on interventions that limit cognitive biases.

Thaler and Sunstein (2008) introduce nudges within this second type of intervention, asserting that they can effectively reduce errors and facilitate behavioral change in a simple and cost-effective way for policymakers. Nudges are environmental interventions that restructure the choice architecture (i.e., the decision-making context) to shape human behavior in a predictable way. Essentially, they steer individuals toward decisions that make their best interests, while maintaining their freedom of choice and keeping all alternatives available (Gajewski et al., 2023). As Thaler and Sunstein (2008) explain, nudges are not prohibitions that impose a certain behavior, but rather a restructuring of the decision environment that promotes the selection of the best option for individuals. The underlying idea is that behavior can be altered by changing the decision-making context, as individuals are not indifferent to the environment when making decisions (Byerly et al., 2018). In other words, the decision frames strongly shape the decision-making process (Glac, 2009). The outcome not only depends on the available information, but it is also influenced by the way such information is provided and, consequently, perceived (i.e., decision frame).

In conclusion, nudges can be viewed as structural interventions that guide behavior by altering the choice architecture. Their distinctive feature lies in their simplicity and cost-effectiveness, allowing human behavior to be influenced with minimal resources while preserving individuals' freedom of choice (Benartzi et al., 2017). However, it should be considered that this approach is not without limitations. Since nudges target actual behavior, they can only achieve changes in the immediate context. In other words, individuals will act as expected only when faced with environmental stimuli. Decision errors can thus be selectively corrected only in specific contexts, where the choice architecture is changed, resulting in a local fix that will persist until the intervention is dismantled (Hertwig & Grune-Yanoff, 2017). In other words, the behavioral change induced by a nudge is context-dependent and transitory. The desired behavior manifests only in the presence of the specific environmental stimuli, and disappears once the individual is no longer exposed to those stimuli.

1.2 Nudges in the context of socially responsible investing

Restructuring the choice architectures in the financial sector could help reduce its inherent complexity and the cognitive demand placed on decision-makers. Indeed, investment decisions often require dealing with risky and uncertain events, limited information available, and complex reasoning processes. Hence, altering the decision environment, for instance presenting information using different formats, can affect the final outcome (Ungemach et al., 2018). However, despite the increasing popularity of nudge interventions in various contexts, such as health and sustainability, the usage of these behavioral change strategies in the investment sector has been quite overlooked (see Cai, 2019 for a review). The same argument can be made for the implementation of nudges in the context of SRI (Hoffmann et al., 2019).

Nudges could be an effective behavioral change strategy in the context of socially responsible investing. Indeed, although the share of SRI has notably increased in recent decades, the market is still primarily dominated by institutional investors, while retail investors account for only a small percentage. Pilaj (2017) suggested that the low participation of private investors in the SRI market could be explained by the unfavorable choice architecture of the decision process. Specifically, the author identified different barriers that could be called in cause as contributing factors.

First, investors could not be aware about the ethical issue within investment decisions. Indeed, when investing, people usually adopt a "money frame", as they tend to primarily focus on financial aspects (e.g., the financial return). Sustainability and ethical information of investment products could be less salient and then ignored (Meunier & Richit, 2023). Prime stimuli could be adopted to activate a “social frame”, thus making these aspects more relevant and increase SRI awareness (Gajewski et al., 2022). Primes can be defined as contextual stimuli (e.g., images or persuasive messages) that influence individuals’ information processing. Previous studies mainly investigated how decision frames influence the choice of SRI (e.g., Glac, 2009; Liu & Peifer, 2022). For instance, Barreda-Tarrazona et al. (2011) showed that priming the ethical aspects of SRI funds enhances the amount invested in responsible assets. Døskeland and Pedersen (2016) reported that investors increase their ethical choices with both financial primes (i.e., information about SRI returns) and ethical prime (i.e., Details about the impact of SRI on sustainability and social issues). This result is consistent with Seifert et al. (2024). The authors found that priming a “money frame”, through SRI financial return information, or a “social frame”, through ESG impact information, promotes in both cases responsible investing. However, presenting a combination of both frames (i.e., money and social frame) at the same time, thus providing financial return and ESG impact information together, produces effects comparable to those observed when the two topics are presented individually. Other studies tested instead (negative) affective priming. Gerkova et al. (2024) reported that inducing feelings of guilt among investors makes them prefer SRI funds and increases the likelihood of sacrificing returns on their investments. Similarly, Gajewski et al. (2022) tested the efficacy of an affective prime, through a banner showing the adverse effect of corporate misconduct, combined with a powerful statement (i.e., "Do you want to profit from this?"). However, this stimulus was quite ineffective. To the best of our knowledge, no studies have yet investigated the effectiveness of priming positive feelings (i.e., positive affective prime) in prompting the willingness to invest in SRI. Finally, priming distant-future mindsets (vs. near-future mindset) notably increases investors' willingness to accept the trade-off between financial performances and social responsibility (Alexander, 2012).

A second potential barrier refers to negative attitudes and beliefs towards SRI. Besides being aware, investors should also have a positive attitude towards sustainability and ethical issues (Pilaj, 2017). Lack of trust and low perceived effectiveness could undermine investors' interest in SRI (e.g., Garg et al., 2022; Jonwall et al., 2023). Similarly, investors believing that SRI products are less profitable than conventional ones, might show negative attitudes as well (Meunier & Richit, 2023). Clarifying information about ESG criteria could have a positive effect on investors' attitudes. Gajewski et al. (2022) tested whether infographics increase socially responsible investing, though reporting a poor effect. Brodback et al. (2021) tried instead labelling to enhance investors' trust towards SRI. In detail, a certification-label of a national organization was applied on some responsible funds. The authors revealed a strong effect of the label on consumers with a low perceived effectiveness on SRI. This finding suggests that ethical labels provided by a neutral public authority can enhance socially responsible investing.

2. Experimental study

Considering the theoretical background previously outlined, an experimental study was designed to test the effectiveness of two nudges in overcoming consumers' barriers towards SRI and influencing investment decisions. Specifically, a nudge was developed for each of the two barriers (i.e., lack of awareness on the ethical aspects of investments and negative attitudes towards SRI) suggested in the theoretical framework proposed by Pilaj

(2017). A first nudge focused on priming a “social mentality”, by making investors more aware about the sustainability and ethical issues of their financial choices. Instead, through a second nudge, our purpose was to enhance trust attitudes towards socially responsible investing.

A 3 X 1 between-subjects design was implemented. One of the three conditions served as the control, while one nudge was adopted for each experimental condition. Participants were randomly assigned to one of the three conditions, to take into account any potential difference other than the treatment between conditions. The experimental task consisted of navigating through a fictional website of an imaginary bank to simulate a hypothetical investment scenario. Participants were required to explore the website page of the fictional bank, carefully evaluating the different choice alternatives and the provided information for the investment funds. To make the experimental setting as realistic as possible, the bank was provided a name (i.e., Fides Bank), a logo, and brand colors. Additionally, filler details, such as bank service overviews, images, and the page header, have been added to the website. The three website versions are available in Appendices (see A. 4).

2.1 Experimental setting

To collect the preference for sustainable investment products, participants could choose to invest within six funds presented on the website. The proposed investment products differed in three relevant details: (i) the level of risk (on a scale ranging from 1 to 7, in accordance with the MiFID directives); (ii) the annual financial performance; (iii) the ESG score (on a scale ranging from 1 to 7) used to classify sustainable financial products. As reported in Table 1, the level of risk was categorized as low (with a score of 2 out of 7), medium (with a score of 4 out of 7), and high (with a score of 6 out of 7). For each investment product, the share of stocks (in percentage) was also reported. Similarly, the ESG score varied between low (score of 3 out of 7) and high (score of 6 out of 7). Thanks to the combination of riskiness and sustainability, two funds for each risk level (i.e., low, medium, and high) were available, with one representing the conventional option (i.e., low ESG score) and the other its responsible alternative (high ESG score). Finally, as for the financial performance (expressed in percentage), we ensured that for each of the three risk levels, the ESG funds slightly underperformed their conventional counterparts, to emphasize the trade-off between financial return and the ethical consideration of the investment decision. An example of fund information is represented in Figure 1.

Table 1.

Characteristics for the six investment products displayed in the website

Fund	Risk	Annual performance	ESG score
Fund 1	2/7 (low) - 10% stocks	10.68%	3/7 (low)
Fund 2	2/7 (low) - 10% stocks	10.09%	6/7 (high)
Fund 3	4/7 (medium) - 40% stocks	16.24%	3/7 (low)
Fund 4	4/7 (medium) - 40% stocks	15.57%	6/7 (high)
Fund 5	6/7 (high) - 80% stocks	21.86%	3/7 (low)
Fund 6	6/7 (high) - 80% stocks	20.12%	6/7 (high)

Participants were asked to invest a fictional capital according to their preferences, without any requirement to invest the entire amount and with the freedom to allocate portions of their capital across the six different funds. Before navigating the website, a screen displayed the experiment instructions and a definition about ESG criteria and SRI. Participants were asked to imagine themselves in a specific scenario, in which they had €10,000 in savings and wanted to invest an amount of money, to achieve their financial goals, with a time horizon of 10 years. An empty box was provided below each fund, to let participants insert the amount of money they wish to allocate. Next to the box, the percentage of the sum invested, relative to the total savings (i.e., 10.000€), was automatically calculated. The available balance was updated in real time as well, deducting the amounts invested each time. This enabled participants to always know the remaining balance available to distribute within the six funds.

The two experimental conditions varied from the baseline in terms of how the choice architecture of the website was restructured. Differences between conditions concerned the adoption of prime stimuli to activate a “social frame”, instead of a “money frame” within participants (condition 1), and the usage of an institutional label to increase trust attitudes towards SRI (condition 2). The first experimental condition was designed to increase awareness of the sustainability and ethical issues in investors' choices, and the second condition was designed to promote positive attitudes toward SRI. In other words, behavioral interventions were developed to specifically address the psychological barriers to SRI identified by Pilaj (2017).

Figure 1.

Example of fund information for control and experimental condition 1

The purpose of condition 1 (i.e., banner condition) was to test the efficacy of a banner in influencing investment decision making. Banners are visual elements, often designed with persuasive language and eye-catching graphics, typically used in websites to convey key information or draw attention to particular contents. Companies adopt banners with advertising and non-advertising purposes. In the second case, they are located in webpages to encourage specific actions. A banner was included in each of the three webpage versions (i.e., control and the two experimental conditions), just above the six investments products, even though condition 1 presented a treatment banner. Indeed, this banner aimed to increase consumers' awareness about ethical and sustainability issues, thus priming a "social frame" instead of a "money frame". Both versions of the banner (i.e., neutral prime and affective prime) were composed of a figure in background and a verbal claim. The neutral banner (used in control and experimental condition 2) reported a self-interested claim about the importance of investing for one's own future financial plans (i.e., "Plan your future. Join the clients that choose investing with us"). The background image depicted a modern building (see Figure 3). The treatment banner was studied instead to evoke an ethical frame, by using a natural landscape as background and an altruistic claim (i.e., "Be part of the change. Join our clients investing in sustainable financial products to build a stable future and protect the planet").

The choice to opt for a figure with natural elements and wind turbines was not casual. Indeed, these kinds of images are frequently used in corporate social responsibility reports, to communicate positive messages, foster trust and legitimacy, and establish an emotional connection with consumers (Invernizzi et al., 2022). To the best of our knowledge, previous studies (Gajewski et al., 2022; Gerkova et al., 2024) only tested affective priming eliciting negative emotions. Therefore, in the present study we aimed at evaluating stimuli

Figure 3.

Representation of the neutral prime banner

Figure 4.

Representation of the affective prime banner

priming positive affect. The nudge banner is represented in Figure 4. As well as the first treatment condition, condition 2 reported ESG scores adopting the colored speedometer.

Finally, experimental condition 2 (i.e., label condition) analyzed whether institutional labels can prompt socially responsible investing. As aforementioned, to date there are no standardized guidelines and definitions for ESG criteria, resulting in low accordance between different ratings. This issue could undermine investors' trust towards SRI. To avoid

Figure 5.

Example of fund information for experimental condition 2

skepticism to prevent socially responsible investing, we created a scenario in which a certification label was adopted by the European Commission (EC), together with clear and standardized evaluation procedures. A logo, named "ESG label", was thus created ad hoc. To increase credibility, in designing the logo we recalled typical graphical elements of EC labels, such as the blue and the stars from the flag and the light green retrieved from the EU Organic Logo. The badge was applied only to the funds with high ESG scores. Since participants could not be familiar with the logo, an explanation was also provided (see Figure 5). Participants were told that the logo certified SRI funds and the evaluation process was handled by a third-party and neutral committee adopting standardized criteria.

Table 2 summarizes the experimental design and the choice architecture for each condition. In brief, the control condition displayed the neutral banner, and investment

Table 2.

Stimuli presented in the three versions of the webpage

Nudge	Control	Condition 1	Condition 2
Banner	Neutral prime	Affective prime	Neutral prime
Label	None	None	Yes

products showed no institutional label. Experimental condition 1 (i.e., banner condition) featured the treatment banner, designed to prompt an affective prime, with no label displayed on the investment products. Finally, experimental condition 2 (i.e., label condition) used the neutral banner, and the three ESG funds displayed the EU label.

2.2 Stimuli pretest

Stimuli were pretested on a sample of 38 individuals through an online survey. Since the bank was fictional, the name was created ad hoc. A set of seven potential names (i.e., Fides bank, Argo bank, Alba bank, Amica bank, Legame bank, Olimpia bank, and Serena bank) was prepared to be evaluated by respondents. Since also names could evoke affects, feelings, and beliefs, participants were asked to select, within the list of names, which one best provided (i) a sense of stability and reliability, (ii) a sense of closeness, and (iii) a sense of trustworthiness.

In creating the two banners (i.e., neutral and treatment) for experimental condition 1, both images and claims were pretested. A pool of five images for the neutral condition and seven images for the treatment condition was considered. As for the neutral banner, images displayed modern buildings, while images for the priming banner depicted natural environments along with wind turbines or solar panels. Respondents were asked to evaluate displayed images across several aspects. First, participants rated the extent to which they enjoyed both neutral and treatment images on a 9-step Likert scale. Then, in a comparison between the seven affective prime images, they were asked to select which element (i) best conveyed a sense of sustainability and (ii) was most suitable for use in a website banner. Likewise, a set of potential persuasive claims was presented for evaluation as well. For both neutral and treatment claims (four in each version), respondents were asked to rate (i) how much they enjoyed the claim, (ii) how clear it was, and (iii) how appealing they found it. Participants were also asked to select, among the treatment claim, (i) the statement they enjoyed most and (ii) the one they believed was most effective in promoting SRI. Images and claims reporting the highest preferences were subsequently adopted as prime stimuli.

Finally, to check the credibility of the fictional European ESG label (i.e., experimental condition 2), six experts of various fields (i.e., finance and economics, public policy, and graphics) were contacted to have a professional opinion. After revisiting the logo following experts feedbacks and comments, the label was considered adequate.

Once finalized, the three versions of the webpage were pretested with a sample of eight participants (two per condition). Participants completed the experimental task and then filled out a brief survey to provide feedbacks and assess the clarity of the instructions. Neither the task instructions nor the scenario required additional changes.

3. Methods

3.1 Sample

For research purposes, data were collected using the CAWI (Computer-Assisted Web Interviewing) methodology in November 2024. Participants, recruited through a panel provider, took part in the experiment online. A quota sampling method was employed, ensuring the sample was representative in terms of gender, age, geographical area, and educational level. Participants were required to be at least 25 years old and employed in a stable occupation. No additional inclusion or exclusion criteria were applied. Participants received monetary compensation for taking part in the study.

The total sample (N = 192) was equally distributed by gender (50.5% female). The age of respondents ranged from 25 to 65 years (M = 47.73, SD = 10.88). Regarding education level, most of the sample (50.6%) held a high school diploma, while 28.6% had a university degree, and 20.8% had completed middle school. Participants were drawn from various Italian geographical areas: 48.4% lived in the northern regions of Italy (27.6% in the northwest and 20.8% in the northeast), 25.5% resided in central Italy, and the remaining 26.1% were from the southern regions.

The sample size was determined based on a power analysis conducted using GPower software (v. 3). The analysis aimed to achieve a statistical power of 0.95 with an expected effect size of 0.29, assuming a between-subjects ANOVA with three groups (one control group and two treatment groups).

3.2 Procedure

Participants were randomly assigned to one of three experimental conditions, with quotas controlled to ensure balanced sub-groups based on socio-demographic characteristics (gender, age, education, and geographical region). The study was conducted exclusively via computer, as the website was not optimized for mobile devices.

After providing written informed consent, participants received detailed instructions for the experimental task, which included an explanation of ESG criteria. To verify their comprehension, two checks were implemented: the first assessed their understanding of ESG ratings, while the second comprised three questions covering key scenario information necessary for completing the task (e.g., the available sum to invest). Only participants who passed both checks were allowed to proceed to the investment decision-making webpage. To ensure data quality, responses from participants who completed the investment task too quickly were excluded from the analysis. After completing the task, respondents filled out a brief survey to collect socio-demographic information and control variables.

The experiment took approximately 15 minutes to complete. The study was approved by the Ethical Committee of the Catholic University and adhered to the ethical guidelines of the American Psychological Association (APA).

3.3 Dependent variables

In the experimental task, participants could choose to invest in conventional funds, sustainable funds, or both. Consequently, different dependent variables were analyzed: the total amount invested, the amount invested in conventional funds, and the sum invested in the three ESG funds. Since three conventional funds and three ESG funds were available on the webpage, the amounts invested in these categories were calculated by aggregating the sums allocated to the respective funds. In doing so, "conventional investing" and "ESG investing" variables were created.

However, analyzing only the absolute amount invested in ESG funds could provide partial information about participants' investment decisions. Indeed, it would be particularly challenging to disentangle participants who chose not to invest at all from those who deliberately avoided investing in ESG funds. Similarly, focusing solely on absolute sums does not account for participants who chose to invest only a portion of the available amount. To address these issues, a fourth dependent variable was introduced: the ratio of the amount invested in ESG funds to the total amount invested (named "ESG investing corrected"). This ratio provides a more reliable estimate of participants' investment in ESG funds as it also considers the total sum they chose to invest, thus representing the proportion of the total amount invested by the participant that was allocated to ESG funds.

3.4 Control variables

3.4.1 Sustainable Financial Literacy

Knowledge and skills in financial domains can significantly influence investment decisions (Balloch et al., 2015; Hermanoss & Jonsson, 2021). Therefore, financial literacy was included as a control variable. However, traditional measures of financial literacy do not assess individuals' understanding of sustainable finance. To address this gap, three ad hoc questions were developed to specifically evaluate participants' knowledge of SRI (e.g., "What does the acronym 'SRI' represent in the field of finance?"). A measure of sustainable financial literacy was then created by summing the number of correct responses to these three questions.

3.4.2 Trust Attitudes

As discussed in Chapter 3, trust in SRI can strongly influence decisions to invest in responsible financial assets. To measure participants' trust in ESG ratings and the sustainability evaluations and screening criteria of financial institutions, four ad hoc items were developed (CR = .952). These items included statements such as, "I am confident that sustainable investment products include only companies committed to social and environmental sustainability." Responses were recorded on a 7-point Likert scale (1 = completely disagree; 7 = completely agree).

3.4.3 Personal Norms

The literature emphasizes that individuals who are more committed to social and environmental issues are more likely to invest in SRI (e.g., Garg et al., 2022; Roos et al., 2022). To account for personal values, the six items from the GREEN scale (CR = .954) were adapted to the context of sustainable investments (e.g., “In investment decisions, it is important to consider ethical and moral aspects"). Items were developed on a 7-steps Likert scale (1 = completely disagree; 7 = completely agree).

3.4.4 Financial Risk Tolerance

Investments inherently involve elements of risk and uncertainty, and risk propensity in financial domains can significantly shape investment behavior (Plieger et al., 2021; Robba et al., 2024; Wong et al., 2018). To account for this factor, financial risk tolerance was included as a control variable. The same scale used in the study presented in Chapter 3 was applied, comprising five items (CR = .907) developed on a scale ranging from 1 (completely disagree) to 7 (completely agree).

3.4.5 Socio-Demographic Characteristics

Prior studies (Gutsche et al., 2021; Hood et al., 2014) have demonstrated differences in socially responsible investing based on gender and political orientation, with women and individuals aligned with left-wing ideologies being more inclined to invest in sustainable assets. Thus, they were included as control variables. Specifically, for political orientation, a single-item scale was developed, consisting of an 11-point continuum ranging from left-wing to right-wing (1 = left-wing; 6 = center; 11 = right-wing). To ensure nuanced analysis, political orientation was treated as a continuous variable in the analysis, although it is reported categorically in the sample description for clarity (i.e., scores from 1 to 4 were classified as left-wing preferences; from 5 to 7 as moderated; from 8 to 11 as right-wing preferences). Within the analyses, higher scores indicated stronger preferences for right-wing parties, while lower scores reflect a strong preference for liberal ideologies.

3.5 Data analysis

First, descriptive statistics for socio-demographic characteristics and control variables were calculated for the entire sample and the three sub-groups. Subsequently, confirmatory factor analyses (CFA) were conducted to evaluate the goodness-of-fit of the three psychometric scales (i.e., trust attitudes, personal norms, and financial risk tolerance). Multiple fit indices were checked to assess the models, including the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Standardized Root

Mean Square Residual (SRMR). Additionally, the 90% confidence intervals for RMSEA and the significance of χ^2 tests were examined. The CFA also provided factor scores for the scales, enabling more reliable estimates to be included in subsequent analyses.

After confirming that quantitative variables were normally distributed, four univariate general linear models (GLMs) were estimated. The first model assessed differences among experimental conditions in the total amount invested. The subsequent three GLMs examined differences across conditions for the sums invested in conventional funds, ESG funds, and ratio of ESG investment to total investment (i.e., the proportion of the total amount invested by the participant that was allocated to ESG funds). Control variables were included as covariates in all models. Post-hoc comparisons were performed using Tukey's Honestly Significant Difference (HSD) test.

4. Results

Sample characteristics are summarized in Table 2. Goodness-of-fit indices for the three psychometric scales are reported in Table 3. Given the satisfactory fit, factor scores were saved and used in subsequent analyses. Table 4 presents the correlations among the control variables. No significant differences were found across conditions concerning the total amount invested [F (2, 189) = .931, $p = .396$, partial $\eta^2 = .010$], indicating that the experimental conditions did not affect participants' overall investment behavior. However, when focusing on investments in conventional funds, a significant difference was found in the model [F (11, 180) = 3.572, $p < .001$, partial $\eta^2 = .179$]. Table 5 shows that only personal norms ($F = 11.677$, $p < .001$) and political orientation ($F = 5.345$, $p = .022$) significantly predicted investment in conventional funds. Post-hoc analysis revealed that participants in condition 2 invested significantly less in conventional funds compared to those in the control condition ($p = .044$), while no significant differences were found between conditions 1 and 2 ($p = .877$).

Table 2.

Descriptive statistics of the sample

Variable	Total sample (N = 192)	Control (n = 61)	Condition 1 (n = 63)	Condition 2 (n = 68)
Gender:				
Male	49%	42.6%	47.6%	55.9%
Female	50.5%	57.4%	52.4%	42.6%
Other	.5%	/	/	1.5%
Age:				
25-34	16.6%	18%	14.3%	17.6%
35-44	22.4%	23%	22.2%	22.1%
45-54	24%	26.2%	25.4%	20.6%
55-65	37%	32.8%	38.1%	39.7%
Education level:				
University degree	28.6%	26.2%	20.6%	32.4%
High-school degree	50.5%	47.5%	52.4%	51.5%
Middle-school degree	20.8%	26.2%	27%	16.2%
Geographical area:				
North west	27.6%	26.2%	20.6%	35.3%
North east	20.8%	18%	28.6%	16.2%
Center	25.5%	27.9%	22.2%	26.5%
South	26%	27.9%	28.6%	22.1%

Political orientation:				
Left-wing	32.3%	31.1%	25.4%	39.7%
Moderated	32.8%	36.1%	38.1%	25%
Right-wing	34.9%	32.8%	36.5%	35.3%
Income:				
Less than 10k €	2.6%	/	/	7.4%
10,000 € - 19,999 €	12.5%	18%	11.1%	8.8%
20,000 € - 29,999 €	20.8%	26.2%	22.2%	14.7%
30,000 € - 39,999 €	19.3%	19.7%	20.6%	17.6%
40,000 € - 49,999 €	18.8%	13.1%	17.5%	25%
50,000 € - 59,999 €	6.8%	4.9%	11.1%	4.4%
60,000 € - 69,999 €	5.2%	3.3%	4.8%	7.4%
70,000 € - 79,999 €	2.6%	3.3%	/	4.4%
80,000 € - 89,999 €	1.6%	/	/	4.4%
90,000 € - 99,999 €	1.6%	1.6%	1.6%	1.5%
Over 100k €	2.1%	1.6%	3.2%	1.5%
Not reported	6.3%	8.2%	7.9%	2.9%
Sustainable financial literacy	1.84 (.79)	1.79 (.76)	1.79 (.81)	1.94 (.83)
Trust attitudes	4.27 (1.46)	4.42 (1.41)	4.05 (1.59)	4.33 (1.36)
Personal norms	5.13 (1.31)	5.18 (1.35)	5.06 (1.17)	5.16 (1.39)
Financial risk tolerance	2.93 (1.44)	2.99 (1.41)	2.73 (1.43)	3.06 (1.48)

Note. Means (Standard deviations) are reported.

Table 3.

Fit indices of the Confirmatory Factor Analysis (CFA)

	χ^2	*df*	p	RMSEA (90% CI)	CFI	SRMR
Trust attitudes	2.866	2	.239	.047 (.000, .105)	.999	.005
Personal norms	10.252	9	.331	.027 (.000, .088)	.998	.018
Financial risk tolerance	6.809	5	.235	.043 (.000, .116)	.997	.015

Note. χ^2 = chi-square; *df* = degree of freedom; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residuals.

Table 4.

Correlations between control variables

Variable	1.	2.	3.	4.	5.
1. Sustainable financial literacy	-				
2. Trust attitudes	.287***	-			
3. Personal norms	.201**	.625***	-		
4. Financial risk tolerance	.149*	.190**	.017	-	
5. Political orientation	.152*	-0.158*	-0.256***	.107	-

Note. *p < .05; **p < .01; ***p < .001.

Table 5.

Results of the general linear models

Variable	Conventional investing			ESG investing			ESG investing (corrected)		
	F	p	partial η^2	F	p	partial η^2	F	p	partial η^2
Conditions	2.820	.062	.030	3.700	.027	.039	7.064	.001	.073
Sustainable financial literacy	1.236	.268	.007	1.848	.176	.010	2.842	.094	.016
Trust attitudes	.416	.520	.002	.504	.479	.003	.402	.527	.002
Personal norms	11.677	< .001	.061	9.564	.002	.050	9.444	.002	.050
Financial risk tolerance	.268	.605	.001	.368	.545	.002	1.762	.186	.010
Political orientation	5.345	.022	.029	3.352	.069	.018	6.617	.011	.035
Gender	.106	.900	.013	.211	.810	.002	.102	.904	.001
Condition * gender	1.142	.322	.013	1.436	.240	.016	1.500	.226	.016

Table 6.

Variable	Total sample (N = 192)	Control (n = 61)	Condition 1 (n = 63)	Condition 2 (n = 68)
Total	87.97% (28.39)	89.84% (25.41)^{a,b}	83.97% (34.06)^{a,b}	90% (24.99)^{a,b}
Conventional investing	36.22% (33.79)	42.21% (34.75)^{a}	39.29% (34.91)^{a}	27.99% (30.61)
ESG investing	51.75% (35.06)	47.62% (34.78)^{a}	44.68% (36.56)^{a}	62% (31.85)
ESG investing corrected	57.03% (36.59)	52.71% (36.62)^{a}	46.76% (37.72)^{a}	70.41% (31.63)

Note. Data compared by row. Values with the same subscript letter do not differ significantly from each other (Tukey's HSD adjusted; $p < .05$).

Regarding investments in ESG funds, the overall model was statistically significant [$F(11, 180) = 3.454$, $p < .001$, partial $\eta^2 = .174$], with a significant difference found between conditions [$F = 3.700$, $p = .027$]. Post-hoc analysis indicated that participants in condition 2 invested significantly more in ESG funds compared to both the control condition ($p = .049$) and condition 1 ($p = .012$), suggesting a unique effect of condition 2 on ESG investment behavior. Among the control variables, only personal norms showed a significant effect on investment in ESG funds ($F = 9.564$, $p = .002$). To further assess sustainable investment behavior, a corrected variable representing the proportion of total investment allocated to ESG funds was calculated. The model for this variable was significant, with a substantial effect size [$F(11, 180) = 4.814$, $p < .001$, partial $\eta^2 = .227$]. A significant difference between conditions was found [$F = 7.064$, $p < .001$], with participants in condition 2 showing a higher proportion of their total investments directed toward ESG funds compared to those in the control condition and condition 1. Both personal norms ($F = 9.444$, $p = .002$) and political orientation ($F = 6.617$, $p = .011$) also played a significant role in the model, underscoring their importance in ESG investment decisions. The amount invested in total and by each condition is reported in Table 6.

5. Discussion

The present study aimed at testing the effect of digital nudges in promoting the decision to invest in ESG financial products. Specifically, we investigated whether various interventions, designed to address cognitive and attitudinal barriers, could influence participants' allocation of funds toward ESG investment products. For this purpose, a website of a fictional bank was created. Participants were presented with a hypothetical investment task, given a hypothetical sum of money to invest in six different funds (i.e., three classified as conventional and three as sustainable). To test the effectiveness of nudges different webpages were created with a slightly different choice architecture.

Overall, our findings provide partial support for the effectiveness of nudges in shaping investment behaviors. Specifically, the banner of condition 1 resulted not effective in priming a “social frame”, as participants invested amounts in ESG funds similar to participants in the control condition. Two possible explanations could be drawn to explain the inconsistency of the affective prime. On one side, it could be possible that the banner in the website was not enough salient to influence participants’ investment decisions. For instance, it could be possible that in navigating the website, some participants didn’t pay enough attention to the banner. Another explanation calls in cause current issues of SRI and ESG criteria, such as the lack of transparency and convergent validity for ESG ratings, or the lack of control and standardization towards corporate social responsibility reports. Considering that also previous studies found only marginal effects of nudges aimed at priming ethical aspects of the investment decision, it could be plausible that such nudges are not strong enough to overcome these aspects. It could be possible that only when individuals perceive they can trust ESG ratings they are actually more prone to invest in SRI.

However, the fictional EC label (condition 2) resulted capable of increasing participants’ preference towards ESG funds. In other words, the results revealed significant effects on the allocation of funds between conventional and ESG investments. Participants in experimental condition 2 (i.e., label condition) invested significantly less in conventional funds compared to the control condition. Moreover, participants in this condition allocated significantly more to ESG funds than those in the control and experimental condition 1 (i.e., banner condition). Relying on findings obtained in condition 2 (i.e., label condition), we speculate that having a reliable third-party certification authority, such as the European Commission, could increase individuals’ positive attitudes on SRI, for instance enhancing trust towards ESG rating criteria. This result is consistent with Brodback et al. (2021).

It should also be considered that besides the proposed nudges, also personal norms and political orientation played a relevant role in participants' investment decisions. These findings are consistent with previous literature (Garg et al., 2022; Hood et al., 2014). The significant influence of personal norms and political orientation further underscores the relevance of individual differences in shaping investment decisions. Personal norms were consistently associated with increased investment in ESG funds, highlighting the role of internalized values and ethical predispositions in overcoming perceived trade-offs between financial returns and sustainability. Similarly, the effect of political orientation suggests that broader ideological frameworks influence the degree to which participants prioritize sustainability in their financial decisions. In brief, socially responsible investing is not only a matter of financial decision criteria, such as expected returns, since psychological characteristics also might come into play.

While the findings of this study contribute to understanding how behavioral nudges can promote sustainable investment decisions, some limitations should be acknowledged. First, the experimental setting, while designed to simulate a realistic investment scenario, involved the use of fictional capital. This means that participants' choices could be different in a real-world situation. For research purpose, the study's design simplified the investment decision process by limiting the choice set to six funds and focusing on three main attributes: risk, annual performance, and ESG score. In real-life contexts, investment decisions involve additional information to be considered in the decisional process. Third, the short time frame of the experimental task is incapable of fully capturing the deliberative process that normally characterize investment decisions. Participants were indeed asked to make immediate allocations, which may not necessarily reflect the reflective and iterative decision-making process that occur over extended periods. A final limitation to acknowledge is the exclusive focus on nudges as a behavioral intervention to promote socially responsible investing. Future studies should explore the potential of other behavioral interventions, such as boosting or informative nudges, in the domain of SRI. These approaches may be particularly effective in enhancing consumers' knowledge about sustainable investments and sustainable finance more broadly. Moreover, future research could investigate strategies to counteract sludges, bureaucratic obstacles and business practices that may discourage investors from choosing sustainable financial assets.

In conclusion, this study contributes to the growing literature on behavioral interventions for sustainable finance by examining the effectiveness of targeted nudges in addressing cognitive and motivational barriers to SRI. Our findings suggest that third-party labels (experimental condition 2) might be particularly effective in promoting ESG investments. our results provide evidence that behavioral nudges can help in prompting individuals toward more sustainable investment choices. This insight has practical implications for policymakers aiming to foster a transition toward more sustainable economies, since it highlights the need for a stronger regulamentation towards sustainable finance and ESG ratings.

CONCLUSION

The present doctoral project was born from a fundamental question: Why should individuals invest in sustainable financial assets? Despite the growing interest in SRI, the debate over their financial performance compared to traditional investments remains unresolved. Hence, it is difficult to fully explain what drives investors toward sustainable investment choices from a neoclassical perspective. According to classical financial theories, investors should focus only on rational aspects in their decisions, for instance evaluating the risk-return trade-off or potential profits. This highlights the need for a multidisciplinary approach to grasp the complexity of this rapidly evolving phenomenon.

The integration of behavioral sciences sheds light on topics often overlooked by traditional financial theories: the critical role of psychological and emotional factors in investment decisions. Investors, far from being purely rational as expected by neoclassical theories, can be influenced by a wide range of elements, including personal values, beliefs, and pro-social and pro-environmental attitudes. While a financial perspective alone is incapable of fully explaining socially responsible investing, behavioral sciences could hence provide insightful insights in understanding why people are not necessarily looking for profit maximization. Socially responsible investing is not merely an economic choice, since it also includes ethical aspects.

The findings of this research lead to three main conclusions. First, while financial criteria remain relevant, they are insufficient to fully explain the preference for sustainable investment products. Although perceived risk and expected return play a central role, the results reported in this dissertation suggest that value-driven motivations are equally significant, illustrating how investors' decisions are guided by a combination of economic and ethical aspects. Second, psychological characteristics, such as positive attitudes, personal values, and environmental consciousness, emerge as key drivers steering investment decisions toward sustainable products. This signals a paradigm shift: investors are not necessarily focused on maximizing profits, but could also be motivated by a desire to contribute to a fairer and more sustainable future for the next generations. Investment choices could also be a form of personal expression, a way to manifest one's own values and make a positive impact on society and the environment. Third, there is a crucial need for improved regulation and standardization of ESG criteria, in order to enhance investors' trust towards SRI. The lack of transparency and alignment across ESG metrics might create significant barriers, increasing skepticism toward sustainable financial products. Addressing these shortcomings would not only reduce the risk of greenwashing by companies but also significantly increase the demand for SRI, thus accelerating the shift toward more sustainable financial markets.

In conclusion, this dissertation offers two key contributions to the literature. On one side, it enhances our understanding of the factors underlying the decision to invest in sustainable financial products. By exploring both financial and psychological determinants, this work sheds light on the complex interplay between rational and value-driven motivations that shape socially responsible investing. Additionally, it also tested behavioral interventions, aimed at positively influencing investment towards more sustainable choices. Leveraging insights from behavioral sciences to reshape choice architecture offers a powerful strategy to encourage sustainable financial behaviors and foster greater participation in the market by private investors. This research underscores the multidimensional and profoundly human nature of socially responsible investing. SRI is not merely a question of numbers or returns; it represents a convergence of economics, psychology, and social responsibility. By identifying the psychological and ethical dimensions driving investment decisions, this dissertation provides actionable strategies to bridge the gap between sustainability goals and financial behaviors.

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APPENDICES

Table A.1

Socio-demographic characteristics of the five profiles identified with the LPA

	Profile 1 (n = 80)	Profile 2 (n = 248)	Profile 3 (n = 182)	Profile 4 (n = 265)	Profile 5 (n = 227)
Gender:					
Female	47.5%	63.3%	56%	38.5%	44.5%
Male	52.5%	36.7%	44%	61.5%	55.5%
Age	39.68 (11.15)	37.38 (10.81)	40.79 (9.78)	35.86 (10.99)	34.75 (10.95)
Education level:					
University degree	12.5%	32.3%	40.7%	29.8%	31.7%
High-school degree	61.3%	53.2%	48.4%	51.3%	51.1%
Middle-school degree	26.3%	14.5%	11%	18.9%	17.2%

Table A.2

Learning parameters for the tested algorithms

Algorithm	Learning parameters
Support Vector Machines	C = 100
	Gamma = 0.001
	Kernel = RBF
Artificial Neural Networks	Learning rate = 0. 001
	Optimizer = Adam
	Loss function = Categorical Cross-Entropy
	Epochs = 250
	Batchsize = 16
Random Forests	bootstrap = False,
	max_depth = None,
	max_features = "sqrt"
	min_samples_leaf = 2
	min_samples_split = 3
	n_estimators = 300
XGBoost	colsample_bytree = 0.7
	gamma= 0.15
	learning_rate = 0.3
	max_depth = 2
	n_estimators = 100
	subsample = 0.5

Table A.3a

Means (Standard Deviations) for the indicators included in the LPA on the sub-sample (n = 802)

Variable	Profile 1 (n = 68; 8.5%)	Profile 2 (n = 217; 27.1%)	Profile 3 (n = 196; 24.4%)	Profile 4 (n = 152; 18.9%)	Profile 5 (n = 169; 21.1%)	Total (N = 802)
Trust	2.07 (1.20)	4.56 (1.09)	3.46 (1.35)	4.70 (1.46)	5.77 (1.15)	4.36 (1.63)
Perceived consumer effectiveness	2.19 (.98)	4.45 (.94)	3.85 (1.26)	5.96 (.91)	5.79 (.87)	4.68 (1.52)
Personal norms	2.96 (1.07)	4.54 (.69)	4.76 (.91)	6.08 (.87)	5.89 (.69)	5.04 (1.22)
Perceived behavioral control	3.15 (1.13)	4.52 (.71)	5.42 (.96)	6.54 (.60)	6.03 (.72)	5.33 (1.27)
Financial literacy	2.07 (1.35)	1.88 (1.39)	2.47 (1.27)	2.82 (1.19)	2.17 (1.26)	2.28 (1.33)
SRI knowledge	2.44 (1.57)	4.05 (1.34)	2.17 (1.18)	3.37 (1.61)	5.01 (1.38)	3.53 (1.74)
Financial risk tolerance	2.37 (1.13)	4.15 (.90)	2.15 (1.04)	2.13 (.99)	5.54 (.88)	3.42 (1.68)
Environmental concern	2.92 (.95)	4.50 (.66)	6.07 (.75)	6.47 (.68)	6.05 (.70)	5.45 (1.29)
Connectedness to nature	3.90 (1.79)	4.31 (1.63)	4.47 (1.27)	5.78 (1.13)	5.47 (1.46)	4.84 (1.58)

Note. Means (Standard Deviations) are reported.

Table A.3b

Means (Standard Deviations) for the indicators included in the LPA on the total sample (N= 1,002)

Variable	Profile 1 (n = 80; 7.9%)	Profile 2 (n = 265; 26.5%)	Profile 3 (n = 248; 24.7%)	Profile 4 (n = 182; 18.2%)	Profile 5 (n = 227; 22.7%)	Total (N = 1,002)
Trust	2.10 (1.29)	4.61 (1.13)	3.56 (1.40)	4.95 (1.39)	5.77 (1.15)	4.47 (1.64)
Perceived consumer effectiveness	2.18 (1.02)	4.43 (.94)	3.89 (1.29)	6.03 (.86)	5.87 (.87)	4.74 (1.53)
Personal norms	2.87 (1.09)	4.54 (.68)	4.81 (.92)	6.11 (.83)	5.95 (.72)	5.08 (1.23)
Perceived behavioral control	3.03 (1.15)	4.49 (.73)	5.51 (.98)	6.56 (.59)	6.05 (.73)	5.36 (1.29)
Financial literacy	2.06 (1.32)	1.89 (1.42)	2.45 (1.27)	2.83 (1.18)	2.07 (1.29)	2.25 (1.35)
SRI knowledge	2.43 (1.52)	4.02 (1.35)	2.12 (1.13)	3.37 (1.56)	5.12 (1.38)	3.55 (1.76)
Financial risk tolerance	2.24 (1.13)	4.12 (.99)	2.17 (1.04)	2.13 (1.02)	5.59 (.87)	3.46 (1.73)
Environmental concern	2.92 (.97)	4.49 (.69)	6.11 (.74)	6.48 (.67)	6.08 (.72)	5.49 (1.29)
Connectedness to nature	3.79 (1.82)	4.31 (1.59)	4.46 (1.30)	5.82 (1.09)	5.49 (1.50)	4.85 (1.59)

Note. Means (Standard Deviations) are reported.

A.4 Webpage of the control condition

A.4 Webpage of experimental condition 1

A.4 Webpage of experimental condition 2