How Do Variations in Financial Literacy, Influenced by Demographic Factors, Affect Investment Behavior Among the Belgian Population Aged 18 to 65?

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HOW DO VARIATIONS IN FINANCIAL LITERACY, INFLUENCED BY DEMOGRAPHIC FACTORS, AFFECT INVESTMENT BEHAVIOR AMONG THE BELGIAN POPULATION AGED 18 TO 65?

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List of Abbreviations

CDF	Cumulative Distribution Function
CDs	Certificates of Deposit
Df	Degrees of Freedom
ETFs	Exchange-Traded Funds
EU	European Union
GFLEC	Global Financial Literacy Excellence Center
GVIF	Generalized Variance Inflation Factor
HFT	High-Frequency Trading
INFE	International Network on Financial Education
OECD	Organisation for Economic Co-operation and Development
R^2	R-squared
RCTs	Randomized Controlled Trials
SES	Socio-Economic Status
VIF	Variance Inflation Factor

1. Introduction

1.1. Background and Motivation

In an increasingly complex financial landscape, the capacity to make sound investment decisions has become more essential than ever. At the heart of this capability lies financial literacy—broadly defined as the ability to acquire, comprehend, and effectively apply financial knowledge to make informed financial choices (OECD, 2013). Financial literacy serves as a critical determinant in how individuals manage personal wealth, evaluate risk, and plan for long-term financial security (Klapper, Lusardi, & Van Oudheusden, 2015; Lusardi & Tufano, 2009). Its significance, both at the individual and societal level, is well-documented in the literature. However, despite the growing body of research, the pathways through which financial literacy shapes investment behavior remain insufficiently explored, particularly within distinct national settings such as Belgium.

This study responds to that gap by investigating the relationship between financial literacy and investment behavior in the Belgian context. Although Belgium performs slightly above the European average in terms of financial literacy, notable disparities persist across demographic segments (Deloitte Belgium, 2023; Demertzis et al., 2024). This heterogeneity raises important questions about the extent to which financial literacy translates into effective investment practices.

Accordingly, this thesis aims to examine whether individuals with higher financial literacy are more likely to engage in strategic and informed investment decisions, or whether persistent cognitive biases and structural constraints continue to mitigate its positive effects. By dissecting key dimensions of investment behavior, this research aspires to contribute not only to the academic discourse but also to practical efforts by policymakers and educators seeking to enhance economic participation and financial well-being in Belgium.

1.2. Research Questions and Objectives

This study is guided by a central research question: *"How do variations in financial literacy, influenced by demographic factors, affect investment behavior among the Belgian population aged 18 to 65?"* By addressing this question, the research seeks to contribute to a nuanced understanding of how financial literacy interacts with individual characteristics to shape investment choices in a national context.

To structure this inquiry, the study pursues the following specific objectives:

- To identify varying levels of financial literacy through the implementation of a financial literacy assessment.

- To evaluate how demographic factors—such as age, gender, and socio-economic status—shape financial literacy levels and moderate their effects on investment behavior.

- To assess the impact of financial literacy on market participation, focusing on individuals' approaches to asset allocation and portfolio diversification.

- To analyze the influence of financial literacy on investment strategy preferences, investigating active versus passive investment choices.

- To examine the relationship between financial literacy and investment horizons, distinguishing between short-term and long-term investment orientations.

- To investigate the interaction between financial literacy and risk-taking behavior, assessing how financial literacy influences risk tolerance and aversion.

- To explore the effect of financial literacy on the frequency of investment activity, studying how often individuals engage with financial markets based on their level of financial understanding.

1.3. Thesis Structure and Organization

This thesis is structured into six main sections, each designed to progressively build a comprehensive understanding of the relationship between financial literacy and investment behavior within the Belgian context.

Following this *introductory chapter*, the *literature review* synthesizes the current body of research relevant to the topic. It begins by examining the conceptual foundations of financial literacy and financial education. Subsequently, the review explores how demographic variables contribute to disparities in financial literacy levels. The discussion then shifts to the ways in which financial literacy influences various aspects of investment behavior. This chapter concludes by identifying key gaps in the existing literature, with particular emphasis on the limited empirical evidence available for the Belgian population.

The *methodology* outlines the research design adopted to address the central research question and test the associated hypotheses. It details the data collection process and describes the analytical approach, with particular focus on the two-stage analysis performed using regression models to assess the relationships between financial literacy, demographic factors, and investment behavior.

The *results* presents the empirical findings of the study. It begins with a descriptive overview of the sample, followed by a systematic presentation of the regression results. Each model's outcomes are reported succinctly to maintain clarity and coherence.

In the *discussion*, these findings are interpreted in light of the initial hypotheses and broader theoretical framework. This chapter also considers the practical implications of the results for policymakers and educators, while acknowledging the study's limitations and proposing directions for future research.

Finally, the *conclusion* synthesizes the main insights derived from the research, reflecting on their significance within the wider discourse on financial literacy and investment behavior.

2. Literature Review

This chapter synthesizes key literature relevant to financial literacy, beginning with its conceptual foundations and measurement approaches. It then explores the role of financial education—both its perceived necessity and the effectiveness of existing programs—before examining how financial literacy varies across demographic groups. Finally, the review assesses the relationship between financial literacy and investment behavior, a critical yet understudied area in the Belgian context. By identifying this gap, the literature review sets the stage for the present study's contribution to understanding how financial literacy shapes investment decisions in Belgium.

2.1. Conceptualizing and Measuring Financial Literacy

Financial literacy is increasingly recognized as a cornerstone of personal and societal financial well-being, yet its definition and assessment remain deeply contested. This section critically examines the evolving conceptual frameworks and interrogates the methodologies used to measure financial literacy across diverse populations.

2.1.1. The Divergence of Views in Financial Literacy

Financial literacy is conventionally defined as the capacity to acquire, comprehend, and apply financial knowledge to make informed decisions regarding personal finances (OECD, 2013). However, this seemingly straightforward definition conceals a more intricate and contested conceptual landscape. Scholars have debated financial literacy through three primary, yet interdependent, dimensions: financial knowledge, decision-making, and behavior. These dimensions, while reinforcing each other, also expose tensions in how financial literacy is understood, measured, and cultivated.

Financial knowledge is often posited as the bedrock of financial literacy. Lusardi and Mitchell (2011) frame it as an understanding of core financial principles—such as compound interest, inflation, and risk diversification—arguing that such knowledge equips individuals with essential tools for fundamental financial tasks, including budgeting, saving, and debt management. Behrman et al. (2012) extend this perspective, contending that financial literacy must encompass a broad and adaptive knowledge base that evolves with the complexities of modern financial systems. This solid base of financial knowledge is particularly crucial for accumulating wealth effectively, especially for long-term financial goals such as retirement. Yet, this knowledge-centric view faces challenges: as Klapper, Lusardi, and Panos (2012) demonstrate, knowledge gaps exacerbate financial vulnerability, particularly during economic downturns, thereby raising concerns about the adequacy of existing financial education in fostering true financial resilience[1]. This critique implies that knowledge alone, while necessary, is insufficient in safeguarding financial well-being.

A more pragmatic approach shifts the focus from knowledge acquisition to its application in financial decision-making. The Organisation for Economic Co-operation and Development (OECD) argues that financial literacy must extend beyond theoretical understanding, incorporating the practical skills required to make informed financial choices (OECD, 2011). Harrison (2016) reinforces this argument, suggesting that effective financial decision-making demands a set of cognitive tools that help individuals navigate diverse financial scenarios. This perspective challenges the assumption that knowledge automatically translates into action, highlighting the importance of decision-making competencies in real-world financial contexts.

[1] Financial resilience can be understood as an individual's capacity to rely on both internal strengths and suitable, accessible external resources when facing financial hardship (Salignac et al., 2019)

Yet, this emphasis on decision-making invites further scrutiny: it assumes that individuals act rationally when making financial choices, an assumption that behavioral finance research increasingly questions.

The behavioral dimension of financial literacy exposes a crucial gap between financial knowledge and financial action. Capuano and Ramsay (2011) argue that even individuals with substantial financial knowledge often fail to make optimal financial choices due to cognitive biases[2] and constraints. This aligns with Fernandes et al. (2014), who critique conventional financial education programs for their over-reliance on knowledge dissemination without adequately addressing behavioral impediments. They advocate for interventions that not only inform but also reshape financial behaviors by mitigating biases. This behavioral-centric critique challenges the foundational premise that financial literacy is merely a function of knowledge accumulation, instead positing that it must be deeply integrated with an understanding of human behavior.

Given these competing perspectives, a growing body of literature calls for a more holistic and integrative approach to financial literacy. The OECD/International Network on Financial Education (INFE) 2023 International Survey of Adult Financial Literacy underscores the necessity of addressing knowledge, decision-making, and behavior as interconnected rather than isolated elements (OECD, 2023). Lusardi and Streeter (2023) further contend that true financial literacy entails not just understanding financial concepts but also the capacity to apply them effectively within the constraints of real-world psychological and economic environments. This integrative approach suggests that financial literacy initiatives must transcend traditional education paradigms, incorporating behavioral insights to enhance financial decision-making and long-term financial resilience.

Regardless of these advancements, financial literacy remains an elusive and contested construct, with no universally accepted definition. The lack of a standardized framework complicates efforts to assess financial literacy, leading to inconsistencies in measurement and policy interventions.

2.1.2. Global Tools for Assessing Financial Literacy

The challenge of measuring financial literacy remains a central concern in the literature, as different methodologies capture distinct dimensions of financial competence. The fundamental question is not merely how financial literacy is assessed, but what each measurement approach implicitly prioritizes.

A dominant approach in financial literacy measurement is the three-question test developed by Lusardi and Mitchell (2011), which evaluates understanding of compound interest, inflation, and risk diversification. Its simplicity and robustness have contributed to its widespread adoption across diverse populations, reinforcing its status as a standardized baseline measure (Global Financial Literacy Excellence Center, 2025a). However, this very simplicity has drawn criticism for its limited scope, as it prioritizes cognitive knowledge over behavioral financial competence.

In contrast, the OECD's INFE framework extends beyond knowledge-based assessments by incorporating financial attitudes and behaviors (OECD, 2022). This tripartite model represents a more holistic perspective, acknowledging that financial literacy is not solely about theoretical comprehension but also about practical financial habits and perceptions. The OECD's broader approach aligns with contemporary research advocating for behavioral finance perspectives, which argue that knowledge alone does not necessarily translate into sound financial decision-making (Fernandes et al., 2014).

[2] Cognitive bias refers to systematic and predictable deviations from rational judgment or decision-making, often resulting from the way the human brain processes information (Blanco, 2017).

A parallel yet complementary global initiative is the Standard & Poor's Global Financial Literacy Survey, which, in collaboration with the World Bank, Gallup World Poll, and the Global Financial Literacy Excellence Center (GFLEC), assesses financial literacy across 140 countries (Global Financial Literacy Excellence Center, 2025b). Its focus on basic numeracy, compound interest, inflation, and risk diversification aligns it closely with both Lusardi and Mitchell's framework and the OECD's measures (Klapper, Lusardi, & Van Oudheusden, 2015). Notably, while these surveys provide invaluable cross-country insights, their reliance on standardized questions raises concerns about cultural bias[3], as financial systems and attitudes toward money vary significantly across regions.

At the European level, the Flash Eurobarometer 525 Survey, conducted by the European Commission, represents the first comprehensive assessment of financial literacy across all 27 European Union (EU) member states, addressing a key gap left by previous national studies that lacked a unified approach. The survey evaluates financial literacy through four key categories—self-assessed financial knowledge, actual financial knowledge, financial behavior, and financial outcomes—providing a multidimensional view of citizens' financial capabilities. The results indicate that, on average, 52% of EU citizens demonstrate financial literacy, with Romania reporting the lowest level at 36%, while Finland leads with 73%. In Belgium, 55% of the population meets the financial literacy threshold. This survey offers valuable comparative data across member states, supporting policy initiatives like the Capital Markets Union[4] (Demertzis et al., 2024). However, its reliance on self-reported data, common in large-scale financial literacy surveys, limits its accuracy. Social desirability bias, where respondents may exaggerate their financial knowledge to align with social expectations, continues to be a significant drawback (Tullis & Albert, 2013). For instance, a study commissioned by Febelfin, the Federation of the Belgian Financial Sector, and conducted by Indiville, a Belgian research and consultancy agency, found that Belgians self-assess their financial knowledge at 6.8/10, yet many tend to overestimate their actual literacy (Febelfin, 2023; Indiville, 2025).

Nevertheless, such assessments often overlook the granular financial challenges faced by specific subgroups. To address these gaps, scholars have developed targeted financial literacy assessments tailored to distinct populations and contexts. For instance, Méndez Prado et al. (2022) constructed a financial literacy scale specifically for young adults, acknowledging that financial challenges in early adulthood differ significantly from those in later life stages. Similarly, behavioral-focused instruments examine the cognitive biases influencing financial decision-making (Asaad, 2015). These alternative approaches highlight the growing recognition that financial literacy extends beyond objective knowledge to include behavioral competencies and real-world applicability.

Despite progress in measuring financial literacy, challenges remain in creating tools that capture its full complexity. Future efforts must refine these measures to ensure they reflect the multifaceted nature of financial literacy in today's financial landscape.

2.2. Financial Education in Theory and Practice

As financial systems grow more complex, financial education has gained prominence as both a personal and policy tool. Recent literature highlights the need for programs that go beyond knowledge transfer, integrating behavioral insights and adapting to demographic and national contexts. This section explores the evolving role of financial education and the strategies underpinning its effective implementation.

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[3] Cultural bias is the tendency to interpret and evaluate people or situations through the lens of one's own cultural values and norms, often leading to premature judgments without direct experience (American Psychological Association, 2018).

[4] The Capital Markets Union (CMU) is an EU initiative aimed at creating a single market for capital, facilitating cross-border investment, improving access to finance—especially for SMEs—and enhancing the resilience, inclusiveness, and global competitiveness of the European economy (European Commission, 2025).

2.2.1. The Critical Role of Financial Education in Modern Economies

In light of growing financial complexity, research has underscored the pivotal role of financial education in enhancing personal financial decision-making, mitigating socioeconomic disparities, and reinforcing macroeconomic stability. As a result, the literature positions financial education as both a microeconomic imperative and a macroeconomic stabilizer.

A fundamental premise in financial education research is its correlation with individuals' financial health[5]. Studies suggest that individuals with higher financial literacy are more likely to engage in sound investment strategies, avoid excessive debt, and accumulate wealth over time (Lusardi & Mitchell, 2014; Lusardi & Tufano, 2009). A national study on financial health conducted by Deloitte Belgium (2023), in collaboration with Ghent University and Argenta, a Belgian bank-insurer, reveals that 64% of Belgian households lack financial resilience—with 36% categorized as financially vulnerable and 28% as financially unhealthy. More than 60% of households face difficulties paying bills, over half do not save regularly, and nearly 50% fail to plan beyond one month. These findings emphasize the urgent need for more targeted financial education and support programs.

Behavioral finance research argues that many financial missteps stem from cognitive biases—such as overconfidence, loss aversion, and herding behavior—which often undermine rational financial decision-making (Bihari et al., 2022). For instance, Barber and Odean's (2001) study on gender differences in investment behavior reveals that overconfidence leads men to engage in excessive trading, ultimately eroding returns. This challenges the notion that financial knowledge alone suffices to improve outcomes; rather, it suggests that educational interventions must also address deep-seated cognitive biases through behavioral insights (Capuano & Ramsay, 2011).

Beyond individual benefits, financial education is positioned as a tool for reducing systemic disparities in financial literacy on a global scale. In both advanced and emerging economies, lower financial literacy levels persist, particularly among certain demographics such as women, lower-income populations, and the less educated. Klapper, Lusardi, and Van Oudheusden (2015) emphasize these disparities and highlight the role of targeted education in fostering financial inclusion and economic empowerment, ultimately breaking cycles of poverty.

On a macroeconomic scale, financial literacy is frequently cited as a stabilizing force that mitigates systemic risks[6]. Buch (2018) contends that a financially literate population is less prone to excessive risk-taking, thereby enhancing economic resilience and reducing—though not eliminating—the likelihood of financial crises.

2.2.2. Designing Effective Financial Education Programs

The OECD's advocacy for financial literacy as a cornerstone of economic stability and individual well-being is well-established, as reflected in its Recommendation of the Council on Financial Literacy. This initiative provides a single, comprehensive framework to support governments, public authorities, and relevant stakeholders in designing, implementing, and evaluating financial literacy policies. It emphasizes evidence-based, context-specific approaches and promotes collaboration across sectors, focusing on three key areas: national strategies for financial literacy, the integration of financial literacy across different sectors of the financial landscape, and the effective delivery of financial literacy programs (OECD, 2020).

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[5] Financial health refers to the overall state of an individual's financial life, reflecting their ability to spend, save, borrow, and plan in ways that promote resilience and long-term well-being (Financial Health Network, 2025).

[6] Systematic risk is the inherent risk that affects the entire market, not just individual stocks or industries (Chen, 2024).

The OECD/INFE 2023 International Survey of Adult Financial Literacy serves as a key instrument in assessing financial literacy disparities across nations, leveraging the OECD/INFE Toolkit for Measuring Financial Literacy and Financial Inclusion 2022 (OECD, 2022). By identifying gaps, the survey provides valuable insights that enable countries and institutions to design targeted interventions aimed at improving financial education (OECD, 2023).

The OECD's historical commitment to financial education is further exemplified by the 2010 OECD-Bank of Italy International Symposium on Financial Literacy. This symposium integrated behavioral economics into financial education discussions, thus contributing to a paradigm shift in program design by recognizing cognitive biases as central to financial decision-making (OECD, 2011). As a result, the OECD-Bank of Italy International Symposium on Financial Literacy has played a crucial role in shaping subsequent financial education initiatives, leading to the development of more comprehensive, evidence-based programs by both public and private organizations.

The case of Belgium provides an illustrative example of a multi-tiered financial education approach, where initiatives target distinct demographic groups. For instance, Wikifin.be, Belgium's official financial education program, provides a platform for the general public with its extensive resources, while also offering Wikifin School, which gives teachers access to educational tools and training. Additionally, the Wikifin Lab offers an interactive learning experience for secondary school students to better understand financial concepts. For professionals, the Febelfin Academy provides a range of training programs to help develop financial knowledge and competencies, covering topics such as banking, investment strategies, compliance, and sustainable finance (Deloitte Belgium, 2023; Febelfin Academy, 2025).

Furthermore, websites like Mijngeldenik.be and Club Beleg, run by Febelfin and Assuralia, the association representing (re)insurance companies operating in Belgium (Assuralia, 2025), provide platforms for young people to seek guidance on money and investment-related questions. The FinFun Games also teach safe online banking and payments (Deloitte Belgium, 2023; Febelfin Academy, 2025). Notably, the Belgian framework aligns with the OECD's emphasis on context-specific strategies, suggesting that financial education programs must be adaptable to national and demographic particularities.

The effectiveness of financial education programs has been widely studied, particularly those evaluated through randomized controlled trials (RCTs)[7], which generally confirm positive outcomes in terms of both knowledge acquisition and financial behavior (Kaiser et al., 2022). Additionally, research by Bernheim et al. (2001) further underscores the long-lasting benefits of early financial education, linking high school financial literacy mandates to improved savings behavior in adulthood.

Initiatives emphasize the importance of flexible approaches, while lasting impact depends on ongoing improvement and cross-sector collaboration. Financial education programs should go beyond information, empowering individuals to navigate today's financial landscape confidently.

2.3. Demographic Determinants of Financial Literacy

Financial literacy is not evenly distributed across populations but shaped by demographic factors such as age, gender, and socio-economic status. While traditional models suggest predictable patterns, emerging research reveals a more complex and sometimes contradictory landscape. This section explores how these demographic dimensions influence financial knowledge, behavior, and resilience.

[7] A randomized controlled trial (RCT) is a prospective, comparative study in which participants are randomly assigned to different intervention groups, enabling the unbiased assessment of cause-effect relationships while minimizing bias and confounding (Bhide et al., 2018).

2.3.1. Age-Based Financial Literacy Patterns

Financial literacy is not a static trait but an evolving competency that fluctuates across different life stages, shaped by shifting financial responsibilities, cognitive development, and experiential learning. The prevailing consensus suggests a life-cycle trajectory wherein financial literacy is lowest among younger adults, peaks in middle age, and subsequently declines in older adulthood (Méndez Prado et al., 2022; Lusardi & Mitchell, 2014). However, this pattern is not universally observed, as recent evidence challenges the assumption of a uniform peak in middle adulthood and raises critical questions about the mechanisms driving financial literacy variations across age cohorts.

In early adulthood, financial literacy is generally underdeveloped due to limited exposure to complex financial responsibilities. Méndez Prado et al. (2022) argue that young adults often lack familiarity with fundamental financial concepts, including managing payments, borrowing, and investing, largely due to minimal real-world financial engagement. This aligns with Henager and Cude (2016), who contend that financial literacy at this stage is hindered by a lack of understanding of crucial financial concepts—such as credit scores, loans, and mortgages. A particularly acute challenge is debt literacy, particularly among younger individuals, who demonstrate notably low levels of financial knowledge, as highlighted by Lusardi and Tufano (2009). This limited comprehension often results in suboptimal financial behaviors, such as excessive debt accumulation and insufficient savings, ultimately undermining long-term financial stability.

As individuals transition into middle adulthood, financial literacy tends to peak, driven by accumulated financial experience and an increase in crystallized intelligence—the capacity to apply learned knowledge to practical financial decisions (Henager & Cude, 2016; Méndez Prado et al., 2022). Lusardi and Mitchell (2011) emphasize that middle-aged adults engage in some of the most consequential financial decisions of their lives, including homeownership, retirement planning, and investment diversification. Saeedi and Hamedi (2018) further assert that the ability to engage in complex financial planning during this stage correlates with superior financial outcomes. However, this assumption of a definitive peak is increasingly scrutinized in light of new findings suggesting that financial health does not always align with expected literacy patterns.

Contrary to the conventional life-cycle model, some research indicates that financial literacy does not universally decline in later adulthood. Cognitive aging undoubtedly plays a role in diminishing financial decision-making capacity and the need for active financial management (Agarwal et al., 2009), yet Kim et al. (2021) highlight that older adults with sustained financial literacy actively compensate for cognitive decline by seeking sophisticated financial advice. Moreover, recent evidence from Demertzis et al. (2024) contradicts the presumed post-middle-age decline, revealing that Belgians over 55 exhibit higher financial literacy scores than younger age groups, challenging the life-cycle hypothesis.

Further complicating the life-cycle narrative, financial resilience patterns do not always correspond with financial literacy trends. Deloitte Belgium (2023) reports an unexpected inversion wherein Belgians aged 18-34 demonstrate greater financial resilience than those aged 35-54. Notably, while individuals over 55 exhibit the highest financial resilience, the 35-54 age group emerges as the most financially unhealthy cohort, with 36% categorized as financially unhealthy, compared to 25% of 18-34-year-olds and 22% of those over 55.

2.3.2. The Gendered Dimensions of Financial Literacy

The impact of financial literacy exhibits notable gender disparities, shaping distinct financial behaviors and decision-making patterns among men and women. While both genders encounter financial challenges, the literature presents a complex interplay between financial knowledge, risk attitudes, and investment behaviors that cannot be reduced to a simple dichotomy of male competence versus female caution. Instead, competing frameworks offer a more nuanced perspective on how financial literacy mediates gendered financial outcomes.

Empirical studies consistently show that men demonstrate higher financial literacy levels than women, a gap that significantly influences financial decision-making (Lusardi & Mitchell, 2011, 2014). Recent research in Belgium reveals that men outperform women by over 20% in financial knowledge assessments, further corroborating the global pattern of gendered financial literacy gaps (Demertzis et al., 2024). This knowledge advantage correlates with greater stock market participation and a higher propensity for financial risk-taking (Van Rooij et al., 2012). However, this observed tendency is not merely a product of financial literacy but also of behavioral biases[8]. Barber and Odean (2001), in their seminal work, argue that male overconfidence exacerbates trading frequency, often leading to suboptimal investment performance. This finding raises the question of whether higher financial literacy translates into superior financial outcomes or whether it merely reinforces a predisposition toward risk-taking. Behrman et al. (2012) support the idea that financial literacy fosters wealth accumulation due to proactive engagement in financial activities. Yet, De Winne and Petkeviciute (2021) challenge the assumption that male-dominated financial activity necessarily equates to superior portfolio management, finding no significant gender differences in overall asset class diversification.

On the other hand, women typically exhibit lower financial literacy levels, which shapes their distinct approach to investments and financial decisions (Lusardi & Mitchell, 2011). This gap extends beyond knowledge acquisition to broader measures of financial resilience, as evidenced by a Belgian study by Deloitte Belgium (2023), which found that only 33% of women were classified as financially resilient compared to 40% of men. Hariharan et al. (2000) have also shown that women tend to adopt conservative investment strategies, favoring financial security over high-yield, high-volatility assets. This cautious approach manifests in lower stock market participation rates among women (Van Rooij et al., 2012), reinforcing the perception of financial conservatism as a gendered trait.

However, behavioral finance research complicates this narrative by highlighting loss aversion as a key differentiator in male and female financial decision-making. Women's heightened sensitivity to potential losses may lead to suboptimal decision-making in certain financial contexts, but it also shields them from the excessive risk-taking associated with male overconfidence (Barber & Odean 2001; Bihari et al., 2022). Paradoxically, while women demonstrate greater prudence, men appear more susceptible to cognitive biases such as mental accounting errors[9], further blurring the link between financial literacy and effective financial behavior (Bihari et al., 2022).

[8] Behavioral biases are systematic deviations from rational judgment, categorized into cognitive biases, stemming from flawed information processing, and emotional biases, which arise from feelings or impulses and are often harder to correct due to their intuitive nature (Worden, 2022).

[9] Mental accounting errors refer to the cognitive tendency to treat money differently depending on its source, intended use, or emotional impact, leading to decisions that often contradict standard economic logic (Pilat & Sekoul, 2021)

2.3.3. Socioeconomic Status as a Predictor of Financial Literacy

Socio-Economic Status (SES) encapsulates an individual's or group's social and economic positioning, commonly assessed through indicators such as income, education level, and occupational status. These components collectively influence one's overall quality of life and access to opportunities (American Psychological Association, 2025; Harrison, 2023). Within this framework, SES plays a pivotal role in shaping financial literacy and the capacity for sound financial decision-making (Nursjanti & Amaliawiati, 2024).

A dominant perspective in the literature posits a strong positive correlation between income and financial literacy. Research by Nursjanti and Amaliawiati (2024) highlights that higher-income individuals exhibit superior financial knowledge, enabling them to engage in more sophisticated financial planning—a claim consistent with the life cycle hypothesis (Kasi et al., 2022). Their findings suggest that while lower-income individuals often struggle with managing daily expenses and face long-term financial difficulties due to inadequate financial knowledge, those with higher earnings are more likely to possess sufficient financial literacy to save or invest for future needs. Empirical evidence from Belgium corroborates this view: wealthier households demonstrate a nearly 30% higher financial literacy score compared to their lower-income counterparts, with financial instability during childhood exerting a lasting detrimental effect on financial health in adulthood (Demertzis et al., 2024; Deloitte Belgium, 2023).

Parallel to income, education emerges as another pivotal determinant of financial literacy, with scholars converging on the notion that higher educational attainment fosters superior financial knowledge (Hastings & Mitchell, 2011; Lusardi & Mitchell, 2014). This disparity is evident across the EU, where, on average, a 23% financial literacy gap exists between highly and less-educated individuals—a divide that becomes even more pronounced in Belgium, exceeding 40% (Demertzis et al., 2024). Advanced education, particularly in finance, economics, or management, is associated with better financial decision-making (Nursjanti & Amaliawiati, 2024). Additionally, early exposure to financial education, such as high school curriculum mandates, has been shown to cultivate responsible financial habits and long-term wealth accumulation (Bernheim et al., 2001). However, the benefits of education are not universally accessible. Individuals with lower educational attainment frequently face challenges in grasping fundamental financial concepts, leaving them more vulnerable to debt mismanagement and economic instability (Lusardi & Tufano, 2009).

The occupational dimension of SES further nuances the debate. The unemployed and those outside the labor force consistently exhibit lower financial literacy compared to salaried employees, reinforcing the idea that economic participation fosters financial acumen (OECD, 2023). However, the relationship between self-employment and financial literacy remains contested. While the OECD (2023) suggests that self-employed individuals generally possess lower financial knowledge than salaried employees, Lusardi and Mitchell (2014) observe a countervailing trend in certain national contexts. Klapper, Lusardi, and Panos (2015) extend this discourse, arguing that higher financial literacy enhances entrepreneurial success by optimizing income management, savings, and debt reduction.

2.4. How Financial Literacy Shapes Investment Behavior

Financial literacy plays a pivotal role in shaping investment behavior across key dimensions such as asset allocation, investment strategy, investment horizon, risk tolerance, and trading frequency patterns. This section examines the complex, sometimes paradoxical, ways in which financial literacy influences decision-making in increasingly dynamic financial markets.

2.4.1. Financial Literacy in Asset Allocation and Portfolio Diversification

Asset allocation, a fundamental investment strategy, involves the deliberate distribution of capital across various asset classes—such as equities, fixed income, real estate, and cash—with the objective of optimizing the trade-off between risk and return in alignment with an investor's financial goals, risk tolerance, and investment horizon (BNP Paribas Wealth Management, 2025). A closely related but distinct concept is diversification, which serves as a risk-mitigation technique by dispersing investments across assets that exhibit low or negative correlations. The underlying premise is that by integrating assets with differing responses to market fluctuations, investors can construct portfolios that reduce overall volatility while preserving return potential (Jayeola et al., 2017).

However, the effectiveness of both asset allocation and diversification is not merely a function of portfolio construction but is significantly shaped by the investor's level of financial literacy. Yang et al. (2022) provide empirical evidence demonstrating that financially literate individuals exhibit a more sophisticated approach to asset allocation, characterized by broader diversification across asset classes. Their findings suggest that greater financial literacy facilitates informed decision-making, allowing investors to construct portfolios that effectively balance risk and reward. Similarly, De Winne and Petkeviciute (2021) reinforce this perspective, arguing that financial literacy enhances investors' ability to recognize the benefits of multi-asset portfolio diversification, leading to a more effective distribution of risk across different asset classes.

The assumption that financial literacy inherently leads to optimal diversification is complicated by cognitive biases in investment behavior, particularly naïve diversification—a heuristic[10] in which investors allocate funds equally across assets without evaluating correlations or risk-return trade-offs. While this approach may appear balanced, it often results in suboptimal portfolios, as equal weighting does not guarantee effective risk management. Low financial literacy exacerbates this issue, as less knowledgeable investors are more susceptible to such biased decision-making, leading to missed opportunities for risk-adjusted returns. As Hanson and Kalthoff (2018) highlight, financial literacy not only mitigates naïve diversification but also enhances security selection by fostering a deeper understanding of risk-reward dynamics, ultimately promoting more informed asset allocation.

2.4.2. Financial Literacy in the Active-Passive Debate

Passive investment funds—such as indexed mutual funds and exchange-traded funds (ETFs)—are designed to replicate market indexes, offering benefits like broad diversification, lower management fees, tax efficiency, and daily portfolio transparency (Carneiro et al., 2020). In contrast, active investment strategies operate on the premise that markets are not perfectly efficient, allowing skilled fund managers to capitalize on mispriced securities (Ofili, 2014).

Yet, historical performance data indicates that passive strategies have generally outperformed active management, primarily because most active fund managers struggle to consistently exceed benchmark returns over extended periods. Nevertheless, many financial experts advocate for a blended approach, integrating both strategies to reduce volatility and improve risk-adjusted returns (The Investopedia Team, 2024).

[10] A heuristic is a cognitive shortcut or simplified strategy used to make decisions or solve problems quickly, prioritizing speed and efficiency over optimal accuracy (Blanco, 2017).

Beyond performance considerations, investor decision-making is significantly shaped by financial literacy. Okicic and Selimović (2020) contend that individuals with higher financial literacy are better equipped to analyze financial information, assess risk, and make strategic investment choices. In line with this perspective, financial literacy empowers investors to engage in active management with greater confidence, potentially leading to superior portfolio outcomes. This view aligns with findings from Van Rooij et al. (2012), who demonstrate that financially literate investors are more likely to own equities, positioning them to benefit from the risk premium associated with stock ownership.

However, despite the advantages conferred by financial literacy, a substantial proportion of knowledgeable investors still gravitate toward passive strategies. This preference suggests that factors beyond financial expertise—such as risk aversion, the recognition of structural limitations and perceived effort required for active management—play a decisive role in investment behavior (Van Rooij et al., 2012).

2.4.3. Financial Literacy and Investment Horizons

Investment horizons, defined as the expected duration for holding an asset before withdrawal, are broadly categorized into short-term and long-term strategies (Chen, 2020).

Short-term investment strategies involve holding assets for periods ranging from a few days to a few years. Investors in this category seek rapid capital appreciation, necessitating active monitoring and quick decision-making to exploit price volatility (Chen, 2020; The Investopedia Team, 2024). In contrast, long-term investment strategies are predicated on sustained capital growth and the compounding effect over extended periods, often spanning decades. Research suggests that the ability to withstand temporary downturns allows long-term investors to achieve superior risk-adjusted returns. Unlike short-term investing, long-term strategies require a more passive approach to monitoring (Chen, 2020; The Investopedia Team, 2024).

Financial literacy plays a dual role in shaping investment horizons, influencing both long-term strategic behavior and short-term trading dynamics. On the one hand, empirical evidence suggests that greater financial literacy enhances individuals' understanding of long-term investment strategies, fostering patient and informed decision-making while lowering barriers to market participation. This relationship goes beyond mere knowledge acquisition; mediation analyses[11] indicate that increased financial awareness actively translates into real investment behavior (Aman et al., 2024). Further reinforcing this, Batra (2024) highlights how financially literate individuals are more inclined toward long-term strategies, as they possess a deeper comprehension of market cycles, compounding, and risk management—key factors that facilitate sustained wealth accumulation.

On the other hand, financial literacy's effects are not uniformly positive. While it helps curb impulsive trading among novice investors, it can paradoxically lead to hyperactivity among highly knowledgeable individuals—a phenomenon attributed to knowledge bias. Overconfidence in one's expertise may prompt excessive trading, which, in some cases, undermines the wealth-preserving benefits of long-term strategies (Aman et al., 2024). Thus, financial literacy's influence on investment behavior is nuanced: it promotes disciplined investing for many, but may also encourage counterproductive short-term activity among a subset of investors.

[11] Mediation analysis is a statistical approach used to examine how an independent variable influences a dependent variable through one or more intermediary (mediator) variables (MacKinnon & Valente, 2019).

2.4.4. The Mediating Role of Financial Literacy in Risk-Taking

Risk perception, the subjective evaluation of an investment's riskiness, is a dynamic construct shaped by cognitive biases and personal experiences. As Ainia and Lutfi (2019) argue, this perception is not merely a rational assessment but is deeply intertwined with emotions and heuristics that influence decision-making under uncertainty. Importantly, risk perception is neither static nor universally uniform; it evolves in response to external stimuli and internal mental states, often leading to discrepancies in investment behavior across individuals. Closely linked to this concept is risk tolerance—the degree to which an investor is willing to accept uncertainty in expected returns. While risk perception governs how individuals interpret potential losses, risk tolerance determines their behavioral response to these risks (Ainia & Lutfi, 2019).

Building on this distinction, Ainia and Lutfi (2019) posit that these two factors exert opposing forces on investment decisions: heightened risk perception tends to deter individuals from high-risk assets, whereas greater risk tolerance predisposes investors toward riskier allocations. This inverse relationship suggests that investors who perceive greater financial risk are more likely to exhibit risk-averse behavior, while those with higher tolerance for uncertainty are more inclined to embrace speculative investments. Supporting this framework, Nguyen et al. (2016) reaffirm the strong correlation between risk tolerance and asset allocation, indicating that risk-tolerant investors are systematically predisposed to invest in higher-risk instruments.

Beyond individual risk attitudes, financial literacy emerges as a pivotal factor that mediates the relationship between risk perception and risk tolerance. Specifically, Aeknarajindawat (2020) underscores the significant positive relationship between financial literacy and risk tolerance, contending that well-informed investors exhibit a greater propensity for risk-taking due to their superior ability to assess and navigate financial uncertainties. This finding introduces a crucial layer of complexity, as financial literacy not only enhances risk tolerance but also modulates risk perception itself. In particular, individuals with higher financial literacy tend to perceive financial risks as more manageable, a phenomenon partly attributable to their greater trust in financial products and markets.

Conversely, financially illiterate investors often exhibit a paradoxical tendency regarding risky assets: although their elevated risk perception discourages market participation, this aversion stems less from a rational evaluation of volatility than from cognitive limitations—such as under-diversification—and a general skepticism toward financial markets. Crucially, this behavior drives them to deliberately avoid risky investments in favor of security over higher returns. As a result, lower financial literacy is associated with reduced holdings of risky assets, fostering more conservative investment strategies (Bucher-Koenen & Ziegelmeyer, 2011).

2.4.5. The Dual Effects of Financial Literacy on Trading Behavior

The concept of trading frequency is central to understanding different market participation strategies, yet it operates within a complex interplay of risk, return, and investor psychology. At the extreme end of the spectrum, High-Frequency Trading (HFT) leverages sophisticated algorithms to execute thousands of trades within microseconds, exploiting fleeting market inefficiencies. In contrast, day traders engage in multiple trades within a single trading day, capitalizing on short-term price movements and intraday volatility. Meanwhile, swing traders take a more moderate approach, holding positions for several days to weeks to capture medium-term price swings. Position traders, who trade the least frequently, maintain positions for weeks or even months, relying on fundamental analysis and long-term trends (Quantra, 2025).

Beyond these technical distinctions, a crucial determinant of trading frequency is financial literacy, which not only influences the choice of trading strategy but also shapes overall investment success (Lusardi & Mitchell, 2014). In fact, empirical evidence suggests that investors with greater financial literacy are more likely to adopt stable investment approaches as they understand the challenges of market timing and the transaction costs associated with frequent trading, resisting the allure of speculative short-term trading (Aman et al., 2024). Conversely, lower financial literacy correlates with an increased propensity for impulsive trading, often reacting to market trends or speculative movements, where investment decisions are driven more by market sentiment and short-term volatility than by rational analysis (Batra, 2024).

However, financial literacy itself is multidimensional, encompassing both objective and subjective components, which introduce additional complexities into trading behavior. Inghelbrecht and Tedde (2024) highlight a paradox: while objectively knowledgeable investors demonstrate a more measured approach to trading, individuals with high subjective financial literacy—those who perceive themselves as well-informed regardless of actual competence—exhibit overconfident behavior, often leading to excessive trading. This dynamic aligns with Barber and Odean's (2001) seminal study, which illustrates that overconfident investors, particularly men, trade more frequently under the illusion of superior stock-picking ability, despite empirical evidence showing that such overactivity erodes returns.

2.5. Research Gaps in Belgian Financial Literacy Studies

While financial literacy has been the subject of a few studies examining its overall state and the demographic disparities influencing its levels in Belgium, there remains a notable gap in research regarding its impact on investment behavior. Addressing this gap presents a significant opportunity to explore the extent to which financial literacy shapes investment choices, trading strategies, and risk preferences among Belgian investors.

A key area for investigation concerns the influence of financial literacy on asset allocation, spanning traditional assets such as stocks and bonds to alternative investments like real estate and cryptocurrencies. Understanding how financial literacy informs these decisions could yield valuable insights into the degree to which Belgians are equipped to navigate the financial world.

Furthermore, it is essential to examine how financial literacy affects investment strategies, particularly the preference for active versus passive portfolio management. Such an inquiry may reveal whether financially literate individuals are more inclined toward active participation in financial markets or whether they exhibit a preference for passive strategies, thereby shedding light on the relationship between financial literacy and investment engagement.

Another critical dimension to consider is the influence of financial literacy on investment horizons. Investigating whether individuals with higher financial literacy are more likely to adopt short-, medium-, or long-term investment perspectives can provide valuable insights into their asset allocation choices and financial goal-setting approaches. These findings would hold important implications for both individual investors and policymakers aiming to promote effective investment planning.

The relationship between financial literacy and risk tolerance also warrants closer examination. Analyzing how financial literacy shapes individuals' comfort with investment risk can inform the development of targeted financial education programs and advisory strategies that support investors in making well-informed decisions aligned with their risk preferences.

Finally, understanding the influence of financial literacy on trading frequency is essential. Determining whether financially literate individuals engage in more frequent trading or adhere to a buy-and-hold strategy can offer significant insights into how financial education influences trading behaviors. This aspect is particularly relevant in assessing whether greater financial literacy correlates with more disciplined and informed investment decisions.

Before exploring these intricate relationships, it is imperative to first re-examine how demographic factors—including age, gender, and SES—shape financial literacy levels in Belgium. A comparative analysis of these findings with both existing Belgian and broader international studies would provide a more nuanced understanding of the demographic determinants of financial literacy within the Belgian context.

By addressing these research gaps, this study aims to offer a comprehensive perspective on the role of financial literacy in shaping investment behavior in Belgium. The insights generated will have important implications for enhancing financial education, empowering individuals to make informed investment decisions, and supporting the development of more effective financial policies and advisory services.

3. Methodology

This chapter outlines the methodological framework used to investigate the relationship between financial literacy and investment behavior, influenced by demographics. It begins by presenting the research hypotheses and theoretical foundations that guide the study. The subsequent sections detail the data collection process, including the sampling strategy and survey design, followed by a description of the variables and coding procedures. Finally, the chapter explains the statistical techniques employed to test the proposed hypotheses and ensure model adequacy.

3.1. Research Hypotheses and Theoretical Foundations

The central research question guiding this study is: "*How do variations in financial literacy, influenced by demographic factors, affect investment behavior among the Belgian population aged 18 to 65?*" This inquiry seeks to elucidate the relationship between individual levels of financial literacy and corresponding investment behaviors, with a particular emphasis on the moderating effects of demographic variables.

To address this research question, the study was structured around a series of hypotheses that delineate the relationships among the core variables.

- H1: Demographics significantly influence financial literacy.

    - H1a: Age significantly influences financial literacy, with younger individuals generally exhibiting lower levels of financial knowledge, which gradually increases in middle adulthood but declines in later years.

This hypothesis is underpinned by the notion that financial acumen is shaped by life experience and exposure to financial decision-making, which tend to accumulate with age, peak during middle adulthood, and decline in later years due to diminishing cognitive abilities and reduced engagement in complex financial activities (Agarwal et al., 2009; Henager & Cude, 2016; Méndez Prado et al., 2022).

    - H1b: Gender significantly influences financial literacy, with men typically exhibiting higher levels of financial literacy compared to women.

This proposition is informed by empirical evidence indicating gender-based disparities in financial knowledge. Studies have consistently shown that men outperform women in financial literacy assessments, which may be associated with a greater propensity among men for investment participation and risk-taking, whereas women often adopt more conservative financial strategies (Hariharan et al., 2000; Lusardi & Mitchell, 2011; Van Rooij et al., 2012).

    - H1c: Socio-Economic Status (SES) positively influences financial literacy, such that individuals with higher SES—measured in terms of income, education, and occupational prestige—tend to possess superior financial knowledge.

Research suggests that individuals from higher SES backgrounds benefit from greater access to financial education and informational resources, thereby enhancing their financial competence (Bernheim et al., 2001; OECD, 2023; Nursjanti & Amaliawiati, 2024).

- H2: Greater financial literacy positively influences asset allocation and portfolio diversification.

This hypothesis is premised on the assumption that individuals with elevated levels of financial literacy are more adept at evaluating risk-return trade-offs and consequently adopt more diversified investment strategies (De Winne & Petkeviciute, 2021; Yang et al., 2022). Financially literate investors are presumed to make more informed decisions across a spectrum of asset classes, ranging from traditional savings to sophisticated instruments such as hedge funds or venture capital.

- H3: Higher levels of financial literacy are positively associated with the likelihood of engaging in active investment strategies over passive ones.

This proposition suggests that financially knowledgeable individuals possess the analytical capacity to process complex financial information, which likely leads to engaging in active investment strategies as it requires more involvement and decision-making (Okicic & Selimović, 2020).

- H4: Individuals with greater levels of financial literacy are more likely to adopt long-term investment strategies rather than short-term trading.

This hypothesis posits that financial literacy enhances an individual's understanding of long-term wealth accumulation mechanisms—such as compounding and market cycles—leading them to favor enduring investment approaches over short-term speculation (Aman et al., 2024; Batra, 2024).

- H5: Higher financial literacy is positively correlated with higher risk tolerance.

Financially literate individuals are hypothesized to exhibit greater confidence in assessing and managing investment risks. As a result, they are more comfortable engaging with higher-risk financial instruments, while simultaneously mitigating perceived risks through informed decision-making (Aeknarajindawat, 2020).

- H6: Greater levels of financial literacy are associated with lower trading frequency, avoiding excessive trading.

This hypothesis suggests that increased financial literacy is linked to more stable and disciplined investment practices. Such individuals are less likely to engage in high-frequency trading behaviors, which are often characterized by elevated transaction costs and speculative tendencies (Aman et al., 2024; Batra, 2024).

To empirically examine these associations among the study variables, a quantitative, correlational research design was employed. This methodological approach facilitated the analysis of the strength and directionality of relationships between demographic variables, financial literacy, and multiple dimensions of investment behavior. These dimensions include asset allocation, engagement in active versus passive investment strategies, investment horizons, risk tolerance, and trading frequency. By focusing on the Belgian adult population aged 18 to 65, the study sought to generate contextually relevant insights with implications for both policy and practice in the domain of financial education and investment decision-making.

3.2. Data Collection and Sampling

This study was based on primary data collected through the administration of a structured survey instrument. The data collection process was conducted using an online questionnaire designed via Google Forms, which was implemented virtually from late December 2024 to mid-March 2025. To maximize participation, the survey link was publicly distributed through various social media platforms and to personal acquaintances, who were subsequently encouraged to share it within their own social networks. This approach, aligned with a snowball sampling technique, was instrumental in increasing the number of respondents.

To facilitate accessibility and inclusivity, the questionnaire was developed as an anonymous, multiple-choice survey available in both French and English. This bilingual format was intended to accommodate a broader demographic of participants across Belgium. The survey instrument was composed of three main sections that aimed to gather comprehensive data relevant to the research objectives.

- Demographics: The first section captured demographic information, including nationality—used to confirm the eligibility of respondents as Belgian nationals—along with age, gender, educational attainment, occupational status, and income. These demographic variables were essential for contextualizing the findings and for analyzing the potential influence of individual characteristics on financial literacy.

- Assessment of Financial Literacy: The second section incorporated the widely recognized "Big Three" financial literacy questions developed by Lusardi and Mitchell, alongside two additional questions to further gauge participants' understanding of basic financial principles. This section served as a critical component in evaluating the level of financial knowledge among the respondents.

- Investment Behavior: The third section addressed participants' investment behaviors. It investigated various aspects such as the types of financial instruments in which respondents invested, their preference for active versus passive investment strategies, investment horizons, risk tolerance, and trading frequency.

The full version of the questionnaire is provided in *Appendix 1*.

In terms of sampling, the study employed a non-probability, voluntary response sampling[12] method. Participants self-selected into the study by choosing to respond to the publicly accessible survey. While this method facilitated efficient data collection, it also introduced the risk of self-selection bias, as individuals who opted to participate may differ systematically from those who did not. Furthermore, the implementation of snowball sampling, whereby respondents were encouraged to forward the survey to their own contacts, helped increase the sample size but may have introduced additional sampling bias. This is due to the tendency of individuals within social networks to share similar characteristics, potentially limiting the heterogeneity of the final sample (Nikolopoulou, 2023).

Despite these methodological limitations, efforts were made to ensure that the sample remained as relevant and representative as possible within the constraints of the research design. Eligibility was restricted to Belgian nationals aged between 18 and 65 years. Initially, 425 responses were collected. After applying the inclusion criteria, 411 responses were deemed valid and retained for subsequent analysis.

[12] Non-probability sampling is a sampling method where participants are selected based on non-random criteria, such as convenience or other specific characteristics, often used when the population is hard to define or when results are intended for a specific group (Nikolopoulou, 2022).

To confirm the adequacy of the sample size, a standard statistical formula for estimating a population proportion was employed. The calculation was based on a 95% confidence level, an assumed population proportion of 50%, and a margin of error of 5% (Qualtrics, 2025). The computation yielded a required sample size of 385 respondents. Given that 411 responses met the inclusion criteria, the sample size was adequate for analysis.

$$n = \frac{Z^2 \times p \times (1 - p)}{e^2} = \frac{(1.96)^2 \times 0.5 \times (1 - 0.5)}{(0.05)^2} = 384.16 \approx 385$$

where:

- n: required sample size
- Z: Z-score corresponding to the desired confidence level
- p: estimated population proportion
- e: margin of error

3.3. Analytical Approach

Upon the completion of the data collection phase, all survey responses were automatically compiled into a Microsoft Excel spreadsheet, which served as the foundational dataset for subsequent analyses (see *Appendix 2*). The initial stage of data processing involved cleaning and standardization procedures. Responses from individuals who did not possess Belgian nationality were excluded from the dataset. Additionally, to maintain linguistic uniformity across the dataset, responses submitted in English were translated into French. Where free-text entries from multiple-choice questions (e.g., 'Other, please specify') were provided, manual reclassification was undertaken in accordance with a predefined categorical schema (e.g., free-text entries such as 'secretary' were recoded under broader pre-defined categories such as 'job in a non-related finance field').

To enable a structured and organized approach to data analysis, a secondary Microsoft Excel spreadsheet was constructed (see *Appendix 3*). Each respondent was assigned a unique identifier, and summary columns were created for all demographic variables. In the section concerning financial literacy, responses to the five questions were transformed into binary variables, with correct responses coded as 1 and incorrect responses as 0. These binary variables were subsequently aggregated to compute a composite financial literacy score ranging from 0 to 5 for each respondent.

The correct responses to the financial literacy items were as follows:

- “More than 102€”: Reflecting an understanding of compound interest accumulation over time.
- “Less than today”: Indicating awareness of the effects of inflation exceeding interest rates.
- “False”: Denoting accurate knowledge that individual stocks are usually riskier than mutual funds.
- “Yes, and I understand how it works”: Demonstrating comprehension of the concept of compound interest.
- “Spreading investments reduces risk”: Capturing familiarity with the principle of diversification.

The complete wording of the financial literacy questions and their corresponding response options is presented in *Appendix 1*.

With regard to investment behavior, binary indicators were created to reflect whether a respondent had invested in each specified asset class, namely: savings instruments, stocks, bonds, mutual funds, exchange-traded funds, real estate, derivatives, commodities, cryptocurrencies, hedge funds, private equity, venture capital, collectibles, or none. Investment strategies were categorized as either active (1) or passive (0), with NA indicating non-applicability. The investment horizon was measured using an ordinal scale ranging from 1 (short term) to 3 (long term), with 2 representing a medium-term perspective and NA used for non-applicable responses. Risk tolerance was assessed on a five-point ordinal scale, where 1 indicated being very risk-averse and 5 indicated being very risk-tolerant; intermediate values captured gradations of somewhat risk-averse (2), neutral (3), and somewhat risk-tolerant (4). Finally, trading frequency was coded on a six-point ordinal scale from 0 (never) to 5 (daily), with intermediate values reflecting 1 (rarely), 2 (yearly), 3 (monthly), and 4 (weekly).

Descriptive statistical analyses were initially performed using Microsoft Excel to summarize sample characteristics and key variables. Advanced statistical analyses were subsequently carried out using RStudio. The corresponding R scripts utilized in these analyses are provided in *Appendix 4*.

3.3.1. Assessment of Multicollinearity

To assess the potential presence of multicollinearity among the predictor variables, a comprehensive correlation matrix was computed (see *Appendix 5*). The analysis revealed that income exhibited moderate correlations with age (r = 0.396) and occupation (r = 0.409), alongside a weaker yet theoretically meaningful association with education (r = 0.193). These findings are consistent with extant literature underscoring the interdependence of education, occupation, and income in constituting SES. Specifically, this pattern reflects the sequential structure whereby educational attainment informs occupational outcomes, which in turn influence income levels (American Psychological Association, 2025).

Table 3.1: Sample Correlation Matrix of Demographic Variables

	Age	Gender	Education	Occupation	Income
Age	1	0.14844858	0.1502784	0.4089382	0.3960106
Gender	0.1484486	1	0.06351511	0.2809367	0.1375668
Education	0.1502784	0.06351511	1	0.19486	0.1932138
Occupation	0.4089382	0.2809367	0.19486	1	0.4086025
Income	0.3960106	0.13756683	0.19321384	0.4086025	1

Note. This table presents a subset of the full correlation matrix, limited to key demographic variables to enhance clarity. The complete matrix, provided in Appendix 5, is more comprehensive but less effective in highlighting the specific associations discussed above.

Source: Own analysis

In addition to the correlation analysis, Generalized Variance Inflation Factors (GVIFs) were calculated for each regression model using the adjusted GVIF metric, $\mathrm{GVIF}^{1/(2\times\mathrm{Df})}$, in accordance with the methodological guidance of Fox and Monette (1992). GVIFs generalize the standard Variance Inflation Factor (VIF) to handle predictors with multiple degrees of freedom (Df), offering a broader assessment of multicollinearity; a more detailed explanation is provided later in this chapter. While all adjusted GVIF values remained below conventional thresholds (typically values exceeding 1.6 are considered indicative of potential multicollinearity (Nahhas, 2025)), income and occupation consistently demonstrated comparatively elevated GVIFs, suggesting a degree of collinearity. Given the convergence of theoretical considerations and statistical diagnostics, income was excluded from the final regression models to enhance model parsimony and reduce redundancy among predictors.

3.3.2. Two-Stage Regression Analysis

In alignment with the formulated research hypotheses, the analytical procedure was conducted in two consecutive stages employing multiple regression techniques. The initial stage examined the extent to which demographic variables account for variations in financial literacy scores. Subsequently, the second stage assessed the influence of financial literacy on distinct facets of investment behavior. For categorical variables incorporated into the regression models, the following reference categories were designated: age group (18–24 years), gender (female), educational attainment (high school diploma), and occupational status (unemployed). These categories were chosen as reference groups in accordance with RStudio's default coding scheme, which assigns the first level of each factor variable as the reference category in regression analysis, thereby ensuring consistency and reproducibility in the modeling process.

3.3.2.1. Stage 1: Demographic Predictors of Financial Literacy

To examine the association between individual demographic characteristics and scores of financial literacy, an ordinal logistic regression[13] model was utilized. The dependent variable, financial literacy score, was operationalized as an ordinal measure ranging from 0 to 5, with higher values indicating greater levels of financial literacy. The independent variables incorporated into the analysis consisted of age, gender, educational attainment, and occupational status. This modeling approach examines how likely an individual is to achieve a higher financial literacy score based on the specified demographic predictors.

The ordinal logistic regression model was specified as follows:

$$\log\left(\frac{\mathrm{P(Financial\ Literacy\ Score} > \mathrm{j)}}{\mathrm{P(Financial\ Literacy\ Score} \leq \mathrm{j)}}\right) = \theta_\mathrm{j} - (\beta_1 \times \mathrm{Age} + \beta_2 \times \mathrm{Gender} + \beta_3 \times \mathrm{Education} + \beta_4 \times \mathrm{Occupation})$$

where:

- j: index for thresholds between adjacent categories of financial literacy
- θ_j: estimated cut-points (intercepts) for each threshold
- β_n: coefficients for the demographic predictors in the model

3.3.2.2. Stage 2: Financial Literacy Effects on Investment Behavior

3.3.2.2.1. Asset Allocation Patterns

To analyze the association between financial literacy and the likelihood of engagement in various investment vehicles, a series of binary logistic regression models were employed. In each model, the primary independent variable of interest was the financial literacy score, while demographic factors—including age, gender, educational attainment, and occupational status—were incorporated as control variables to account for potential confounding[14] influences.

[13] Logistic regression is a statistical method used to model the probability of a categorical outcome based on one or more predictor variables by modeling the log-odds of the event. It includes binary logistic regression for two-category outcomes, multinomial logistic regression for outcomes with more than two unordered categories, and ordinal logistic regression for outcomes with more than two ordered categories (Lee, 2025).

[14] In studies exploring potential causal relationships, a confounding variable refers to an unobserved third factor that simultaneously affects both the presumed independent and dependent variables, thereby potentially distorting the observed association (Thomas, 2020).

Separate logistic regression models were estimated for each individual investment product—namely savings instruments, stocks, bonds, mutual funds, ETFs, real estate, derivatives, commodities, cryptocurrencies, and collectibles. The dependent variable in each model was binary, indicating whether the respondent had invested in the corresponding financial asset (coded as 1 for participation, and 0 for non-participation). Given that respondents were permitted to report involvement in multiple asset categories, the models accommodated overlapping investment behaviors and were interpreted independently for each asset class.

The binary logistic regression model for each investment type was specified as follows:

$$\log\left(\frac{\mathrm{P(Investment\ Type = 1)}}{1 - \mathrm{P(Investment\ Type = 1)}}\right) = \beta_0 + \beta_1 \times \text{Financial Literacy Score} + \beta_2 \times \text{Age} + \beta_3 \times \text{Gender} + \beta_4 \times \text{Education} + \beta_5 \times \text{Occupation}$$

where:

- β_0: intercept term
- β_n: coefficients for financial literacy and demographic predictors in the model

In addition to assessing participation in specific investment categories, the study also investigated complete non-participation in financial markets. This was operationalized using a separate binary outcome variable, Investment None, which assumed a value of 1 if the respondent had not engaged in any of the aforementioned investment activities, and 0 otherwise. This outcome was mutually exclusive from all other investment types, providing a comprehensive measure of financial disengagement.

The binary logistic regression model was specified as follows:

$$\log\left(\frac{\mathrm{P(Investment\ None = 1)}}{1 - \mathrm{P(Investment\ None = 1)}}\right) = \beta_0 + \beta_1 \times \text{Financial Literacy Score} + \beta_2 \times \text{Age} + \beta_3 \times \text{Gender} + \beta_4 \times \text{Education} + \beta_5 \times \text{Occupation}$$

where:

- β_0: intercept term
- β_n: coefficients for financial literacy and demographic predictors in the model

Although the dataset permitted robust analysis across common investment types, participation in certain alternative asset classes proved exceedingly rare. Specifically, only five respondents (1.2%) reported investments in hedge funds, ten respondents (2.4%) in private equity, and a single respondent (0.2%) in venture capital. Given the extremely low prevalence of these investments in the sample, conducting statistically meaningful analyses—such as regression models or even robust descriptive statistics—was not methodologically justifiable. The rarity of these events introduced considerable bias, as rare investments were likely underrepresented, while the complementary category of non-investments was overrepresented (King & Zeng, 2001).

Consequently, although the initial research design intended to examine the effect of financial literacy on participation in hedge funds, private equity, and venture capital, these analyses could not be conducted due to data limitations. Future research may address this gap by employing targeted sampling techniques, such as the deliberate inclusion of high-net-worth individuals or institutional investors, to facilitate statistically robust examination of alternative investment behavior.

3.3.2.2.2. Active versus Passive Investment Strategy

To investigate the association between financial literacy and the adoption of a specific investment strategy, a binary logistic regression model was estimated. The dependent variable was a binary indicator, coded as 1 for respondents who have adopted an active investment strategy, and 0 for those who have selected a passive approach. Responses coded as NA were omitted before running the model.

The primary independent variable of interest was the financial literacy score, while demographic factors—including age, gender, educational attainment, and occupational status—were incorporated as control variables to account for potential confounding influences.

The logistic regression model was specified as follows:

$$\log\left(\frac{\mathrm{P(Investment\ Strategy = 1)}}{1 - \mathrm{P(Investment\ Strategy = 1)}}\right) = \beta_0 + \beta_1 \times \mathrm{Financial\ Literacy\ Score} + \beta_2 \times \mathrm{Age} + \beta_3 \times \mathrm{Gender} + \beta_4 \times \mathrm{Education} + \beta_5 \times \mathrm{Occupation}$$

where:

- β_0: intercept term
- β_n: coefficients for financial literacy and demographic predictors in the model

3.3.2.2.3. Investment Horizon Preferences

To examine the impact of financial literacy on individuals' investment horizons, an ordered probit regression[15] model was utilized. The dependent variable, investment horizon, was an ordinal measure representing the temporal scope of an individual's investment plans, categorized as short-term, medium-term, and long-term. Responses coded as NA were omitted before running the model.

The primary independent variable of interest was the financial literacy score, while demographic factors—including age, gender, educational attainment, and occupational status—were incorporated as control variables to account for potential confounding influences.

The ordered probit regression model was specified as follows:

$$\Phi^{-1}\big(\mathrm{P(Investment\ Horizon} \leq \mathrm{j)}\big) = \beta_0 + \beta_1 \times \mathrm{Financial\ Literacy\ Score} + \beta_2 \times \mathrm{Age} + \beta_3 \times \mathrm{Gender} + \beta_4 \times \mathrm{Education} + \beta_5 \times \mathrm{Occupation}$$

where:

- Φ^{-1} : inverse of the standard normal cumulative distribution function (CDF)
- β_0: intercept term
- β_n: coefficients for financial literacy and demographic predictors in the model

3.3.2.2.4. Risk Tolerance

To analyze the association between financial literacy and individuals' risk tolerance, an ordinal logistic regression model was employed. The dependent variable, risk tolerance, was measured on an ordinal scale capturing increasing degrees of willingness to engage in financially risky behavior, ranging from "very risk-averse" to "very risk-tolerant".

[15] Ordered probit regression is a statistical model used to estimate the relationship between an ordinal dependent variable and one or more independent variables, by modeling the probability that a latent continuous variable falls between threshold values corresponding to ordered outcome categories (StataCorp, 2025).

The primary independent variable of interest was the financial literacy score, while demographic factors—including age, gender, educational attainment, and occupational status—were incorporated as control variables to account for potential confounding influences.

The ordinal logistic regression model was specified as follows:

$$\log\left(\frac{\mathrm{P(Risk\ Tolerance > j)}}{\mathrm{P(Risk\ Tolerance \leq j)}}\right) = \theta_j - (\beta_1 \times \mathrm{Financial\ Literacy\ Score} + \beta_2 \times \mathrm{Age} + \beta_3 \times \mathrm{Gender} + \beta_4 \times \mathrm{Education} + \beta_5 \times \mathrm{Occupation})$$

where:

- j: index for thresholds between adjacent levels of risk tolerance
- θ_j: estimated cut-points (intercepts) for each threshold
- β_n: coefficients for financial literacy and demographic predictors in the model

3.3.2.2.5. Trading Frequency

To investigate the influence of financial literacy on individuals' trading frequency, an ordered probit regression model was estimated. The dependent variable, trading frequency, was an ordinal measure capturing the frequency of trading activity, ranging from "never" to "daily", thereby reflecting progressively higher levels of engagement in trading behavior.

The primary independent variable of interest was the financial literacy score, while demographic factors—including age, gender, educational attainment, and occupational status—were incorporated as control variables to account for potential confounding influences.

The ordered probit regression model was specified as follows:

$$\Phi^{-1}(\mathrm{P(Trading\ Frequency \leq j)}) = \beta_0 + \beta_1 \times \mathrm{Financial\ Literacy\ Score} + \beta_2 \times \mathrm{Age} + \beta_3 \times \mathrm{Gender} + \beta_4 \times \mathrm{Education} + \beta_5 \times \mathrm{Occupation}$$

where:

- Φ^{-1} : inverse of the standard normal cumulative distribution function (CDF)
- β_0: intercept term
- β_n: coefficients for financial literacy and demographic predictors in the model

3.3.2.3. Model Adequacy: Goodness-of-Fit and Multicollinearity

Pseudo R-squared values serve as alternative goodness-of-fit measures for regression models where the traditional R-squared statistic is not applicable, such as logistic regressions and other non-linear models. Unlike the classical R-squared, which relies on the sum of squared errors and assumes constant error variance, pseudo R-squared metrics provide analogous insights into the explanatory power of a model in contexts where such assumptions do not hold. Various forms of pseudo R-squared, including McFadden's, have been developed to quantify how well a model accounts for the variability in the dependent variable, offering a useful interpretive tool for assessing model performance in non-linear and non-continuous outcome settings (UCLA: Statistical Consulting Group, 2011).

In each regression model, McFadden's R^2 (Hardin & Hilbe, 2007) was used and computed as follows:

$$R^2_{\mathrm{McFadden}} = 1 - \frac{\mathcal{L}(\mathrm{M}_\beta)}{\mathcal{L}(\mathrm{M}_\alpha)}$$

where:

- M_β: full model (with intercept and predictors)
- M_α: intercept-only model
- $\mathcal{L}(\mathrm{M}_\mathrm{k})$: log-likelihood of model k

According to McFadden's guidelines, values between 0.2 and 0.4 suggest a good model fit, while values exceeding 0.4 are indicative of excellent fit quality (Hemmert et al., 2016).

In addition, multicollinearity among predictors was continuously monitored using the adjusted GVIF. The GVIF extends the conventional VIF framework to accommodate predictor variables with multiple degrees of freedom, thereby offering a more robust measure of variance inflation in such contexts. To ensure comparability across predictors differing in dimensionality, the GVIF was adjusted using the following transformation:

$$\mathrm{GVIF}^{1/(2\times\mathrm{Df})}$$

Where Df denotes the number of parameters estimated for each predictor. This adjustment facilitates equitable interpretation across both continuous and categorical variables (Fox & Monette, 1992).

Adjusted GVIF values exceeding $\sqrt{2.5}$ (approximately 1.6) may reflect moderate levels of multicollinearity, while values surpassing $\sqrt{5}$ or $\sqrt{10}$ (approximately 2.2 and 3.2, respectively) are considered indicative of more severe multicollinearity concerns (Nahhas, 2025).

4. Results

This chapter presents the empirical findings of the study in two parts. The first section provides descriptive statistics that outline the demographic characteristics, financial literacy scores, and investment behavior variables of the sample, offering foundational insights into the dataset. The second section details the results of a two-stage regression analysis: first, exploring the extent to which demographic variables predict financial literacy, and second, examining how financial literacy influences various dimensions of investment behavior. Together, these results inform the study's core investigation into the role of financial literacy in shaping investment decisions.

4.1. Descriptive Statistics

This section establishes the sample's foundational characteristics through systematic analysis of three core dimensions: (1) demographic composition, (2) financial literacy proficiency, and (3) investment behavior patterns. These descriptive statistics provide the empirical basis for investigating subsequent relationships between demographic factors, financial literacy, and investment decision-making.

4.1.1. Demographic Composition

Age Groups

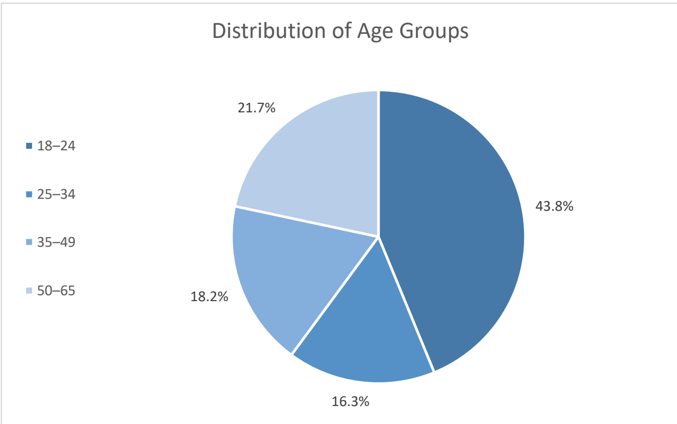

Figure 4.1: Distribution of Age Groups

Source: Own analysis

The respondents were categorized into four age groups: 18–24, 25–34, 35–49, and 50–65 years. The largest proportion of participants fell within the 18–24 age bracket, constituting 43.8% (n = 180) of the sample. This was followed by respondents aged 50–65 (21.7%, n = 89) and those aged 35–49 (18.2%, n = 75). The smallest age cohort was 25–34 years, representing 16.3% (n = 67) of the sample. Overall, the sample exhibited a relatively young demographic composition, with a pronounced concentration of participants in the youngest age group.

Gender Composition

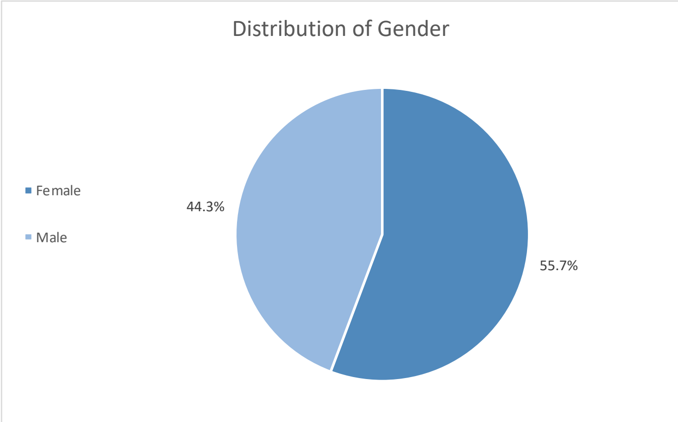

Figure 4.2: Distribution of Gender

Source: Own analysis

The gender distribution of the sample was moderately skewed toward female respondents, who accounted for 55.7% (n = 229) of participants, compared to 44.3% (n = 182) male respondents. Despite this slight disparity, both genders were substantially represented in the dataset.

Educational Attainment

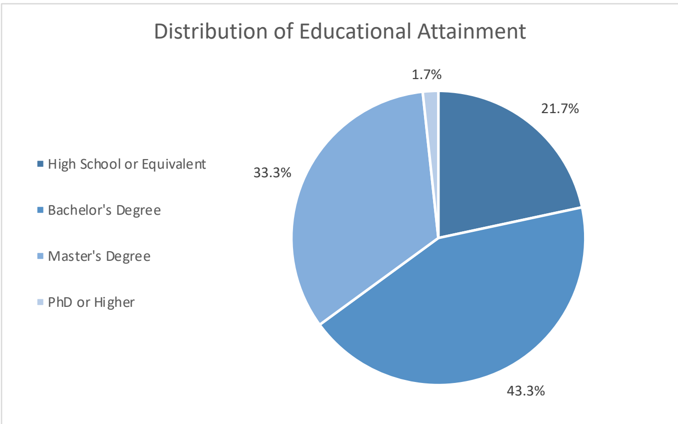

Figure 4.3: Distribution of Educational Attainment

Source: Own analysis

In terms of educational background, the majority of respondents held a bachelor's degree (43.3%, n = 178), followed by those with a master's degree (33.3%, n = 137). A considerable proportion reported a high school diploma or equivalent as their highest qualification (21.7%, n = 89), while a negligible minority possessed a PhD or higher academic credential (1.7%, n = 7). These findings indicate that the sample was predominantly composed of individuals with tertiary education.

Occupational Status

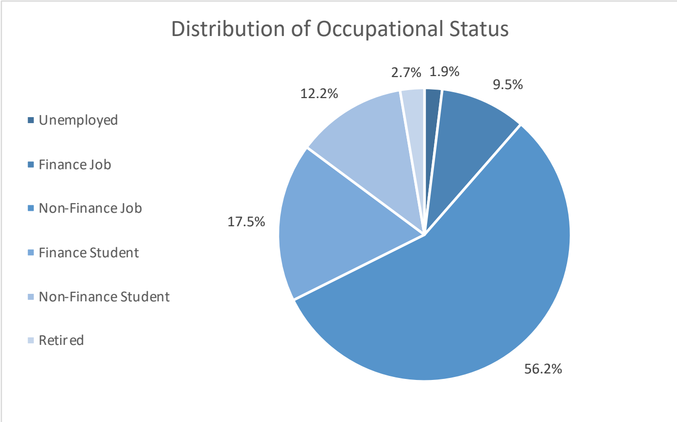

Figure 4.4: Distribution of Occupational Status

Source: Own analysis

The participants represented a diverse range of occupational backgrounds. The largest segment was employed in non-finance-related professions (56.2%, n = 231). Finance students constituted 17.5% (n = 72) of the sample, whereas non-finance students accounted for 12.2% (n = 50). A smaller subset of respondents worked in the finance sector (9.5%, n = 39). Additionally, the sample included a marginal proportion of unemployed individuals (1.9%, n = 8) and retired participants (2.7%, n = 11). Collectively, the occupational distribution reflects a heterogeneous mix of professionals, students, and other employment statuses.

4.1.2. Financial Literacy Proficiency

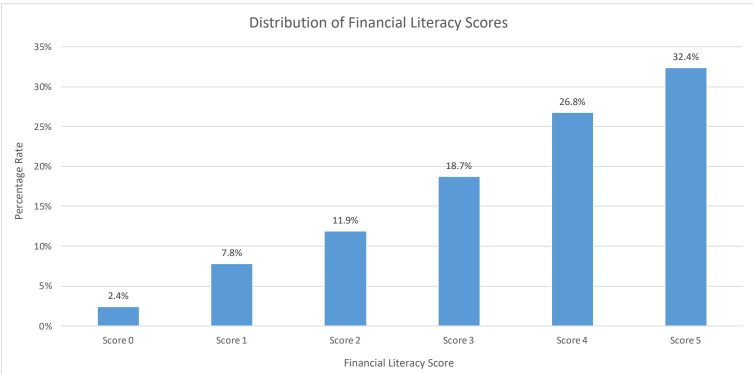

Figure 4.5: Distribution of Financial Literacy Scores

Source: Own analysis

Financial literacy was measured on a scale ranging from 0 to 5, with higher scores reflecting greater financial knowledge. The distribution of scores revealed a strong tendency toward the upper end of the spectrum: 32.4% (n = 133) of respondents attained a perfect score of 5, while 26.8% (n = 110) scored 4. A smaller proportion of participants scored 3 (18.7%, n = 77), 2 (11.9%, n = 49), or 1 (7.8%, n = 32), and only 2.4% (n = 10) scored 0. These findings indicate that the sample exhibited relatively high financial literacy, with nearly 60% of respondents achieving a score of 4 or 5.

4.1.3. Investment Behavior Patterns

Asset Allocation

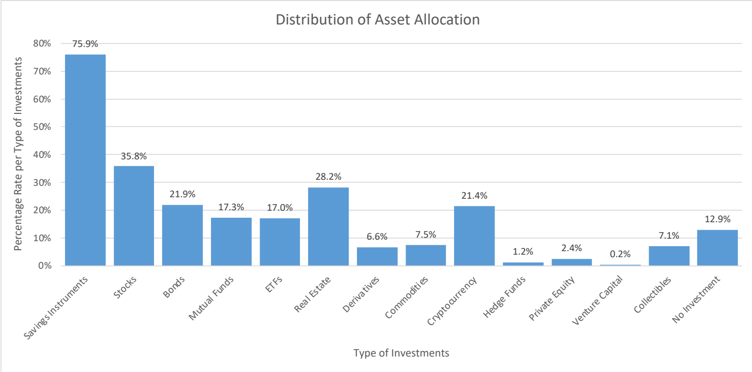

Figure 4.6: Distribution of Asset Allocation

Source: Own analysis

Respondents exhibited a diverse range of asset allocations. The most prevalent holdings were traditional savings products, reported by 75.9% (n = 312) of participants. Stocks constituted the second most common investment (35.8%, n = 147), followed by real estate (28.2%, n = 116), bonds (21.9%, n = 90), and cryptocurrency (21.4%, n = 88). Other financial instruments included mutual funds (17.3%, n = 71) and ETFs (17.0%, n = 70). Less common allocations comprised commodities (7.5%, n = 31), collectibles (7.1%, n = 29), derivatives (6.6%, n = 27), private equity (2.4%, n = 10), hedge funds (1.2%, n = 5), and venture capital (0.2%, n = 1). Notably, 12.9% (n = 53) of respondents reported no investments in financial or tangible assets. These findings indicate a preference for low-risk, traditional instruments, though a substantial minority engaged with more volatile or alternative assets.

Active versus Passive Investment Strategy

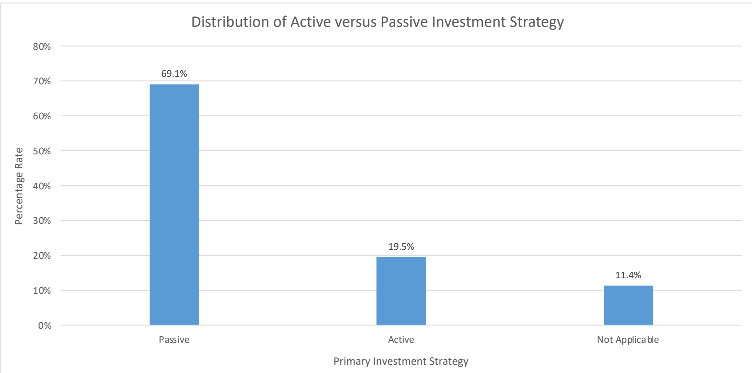

Figure 4.7: Distribution of Active versus Passive Investment Strategy

Source: Own analysis

The majority of respondents preferred a passive investment strategy, with 69.1% (n = 284) favoring this approach. A smaller proportion, 19.5% (n = 80), reported adopting an active strategy, while 11.4% (n = 47) deemed the question inapplicable to their investment behavior. This suggests that passive strategies are the explicit dominant approach within the sample.

Investment Horizon Preferences

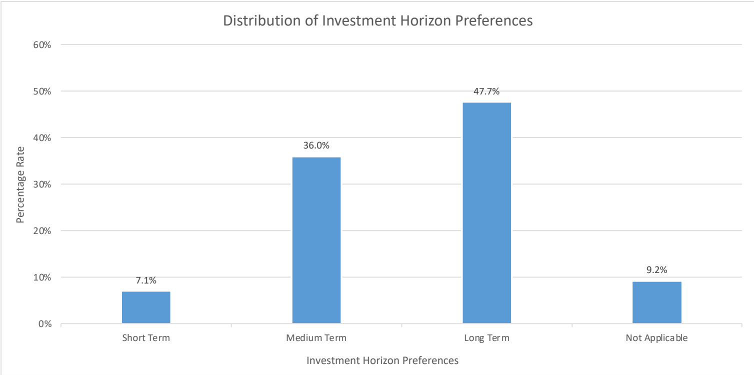

Figure 4.8: Distribution of Investment Horizon Preferences

Source: Own analysis

The majority of respondents favored a long-term investment horizon (47.7%, n = 196), followed by a medium-term horizon (36.0%, n = 148). Only 7.1% (n = 29) opted for short-term strategies, while 9.2% (n = 38) indicated that this question was not applicable to their investment behavior. These findings collectively indicate a pronounced inclination toward longer-term investment approaches within the sample population.

Risk Tolerance

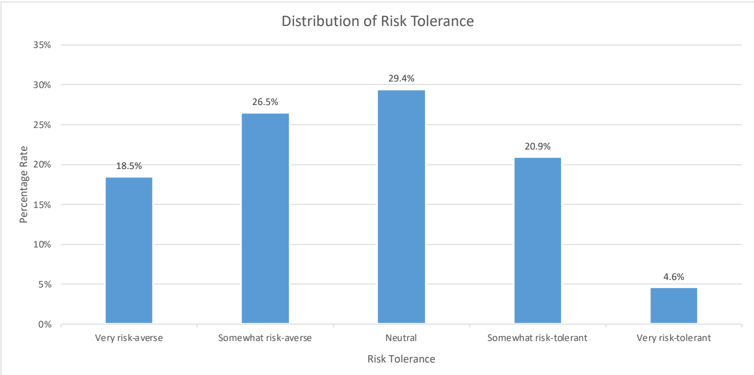

Figure 4.9: Distribution of Risk Tolerance

Source: Own analysis

Risk tolerance levels varied across the sample. The largest cohort (29.4%, n = 121) identified as risk-neutral, followed by somewhat risk-averse (26.5%, n = 109) and somewhat risk-tolerant (20.9%, n = 86) respondents. A smaller proportion reported being very risk-averse (18.5%, n = 76), while very risk-tolerant individuals constituted the smallest group (4.6%, n = 19). Collectively, these results suggest a moderate risk appetite, with a skew toward caution.

Trading Frequency

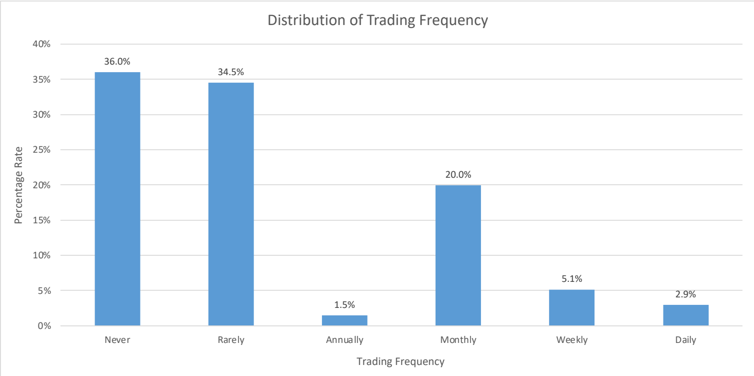

Figure 4.10: Distribution of Trading Frequency

Source: Own analysis

In terms of trading frequency, the majority of respondents reported infrequent trading activities. A significant proportion, 36.0% (n = 148), stated that they never trade, while 34.5% (n = 142) trade rarely. Monthly traders comprised 20.0% (n = 82) of the sample, followed by weekly traders at 5.1% (n = 21), and daily traders at 2.9% (n = 12). Only 1.5% (n = 6) of respondents reported trading annually.

4.2. Two-Stage Regression Analysis

This section presents the results of regression analyses examining two key relationships: (1) the influence of demographic characteristics on financial literacy, and (2) the effect of financial literacy on investment behavior. Detailed regression outputs can be found in *Appendix 6*.

To assess multicollinearity, the adjusted GVIF was computed for each predictor in the regression models. Throughout all models, the adjusted GVIF values remained substantially below the established thresholds, suggesting that multicollinearity did not pose a significant concern in any of the analyses.

4.2.1. Stage 1: Demographic Predictors of Financial Literacy

Table 4.1: Impact of Demographic Variables on Financial Literacy

	Coefficient	Standard Error	Odds Ratio
Age (Linear Term)	-0.1405	(0.2213)	0.869
Age (Quadratic Term)	0.3245	(0.2174)	1.3834
Age (Cubic Term)	0.2988	(0.2230)	1.3482
Male	1.5033***	(0.2134)	4.4965
Education (Linear Term)	1.7761***	(0.5097)	5.9068
Education (Quadratic Term)	-0.1526	(0.3890)	0.8585
Education (Cubic Term)	-0.2414	(0.2289)	0.7855
Finance Job	1.6938*	(0.7394)	5.4401
Non-Finance Job	0.0445	(0.6432)	1.0456
Finance Student	2.3649**	(0.7197)	10.6435
Non-Finance Student	-0.0365	(0.6928)	0.9641
Retired	-0.6182	(0.8291)	0.5389
0|1	-3.6965***	(0.7305)	—
1|2	-1.9988**	(0.6668)	—
2|3	-0.9124	(0.6557)	—
3|4	0.2955	(0.6545)	—
4|5	2.0701**	(0.6630)	—
McFadden R^2	0.1824		

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

The regression model examining financial literacy in relation to demographic variables reported a McFadden R^2 of 0.1824. This suggests the model accounts for approximately 18.2% of the variance in financial literacy scores, indicative of a moderate level of explanatory power consistent with McFadden's criteria for a reasonably good fit.

Age did not emerge as a significant predictor, whereas gender did. Men had 4.5 times higher odds of being in a higher financial literacy category compared to women. Education had a significant linear effect on financial literacy, with each one-unit increase in education level being associated with 5.91 times higher odds of higher financial literacy. The quadratic and cubic terms for education were non-significant, indicating that the relationship between education and financial literacy was strictly linear. Occupation also played a significant role in predicting financial literacy. Individuals working in finance-related professions had 5.44 times higher odds of being in a higher financial literacy category compared to unemployed individuals, and finance students had 10.64 times higher odds. However, individuals in non-finance occupations or retirees did not significantly differ in terms of financial literacy.

Categorical intercepts represent baseline financial literacy scores for distinct groups. Intercepts "0|1" and "1|2" had significantly negative baseline scores, indicating lower baseline financial literacy in these categories, while intercept "4|5" had a significantly positive baseline score, indicating higher baseline financial literacy in this group. Intercepts "2|3" and "3|4" did not exhibit statistically significant baseline differences, suggesting no notable distinction in financial literacy levels between these categories.

4.2.2. Stage 2: Financial Literacy Effects on Investment Behavior

4.2.2.1. Asset Allocation Patterns

Table 4.2: Impact of Financial Literacy on Asset Allocation

	Savings Instruments	Stocks	Bonds	Mutual Funds	ETFs	Real Estate	Derivatives	Commodities	Crypto	Collectibles	None
(Intercept)	3.8401	-3.8185**	-3.2717**	-18.5718	-28.0488	-0.8580	-21.6150	-18.5208	-19.8546	-2.3748^	-5.3131
	(213.6371)	(1.1959)	(1.0864)	(793.5144)	(2044.7517)	(0.9873)	(2149.2102)	(1334.6814)	(1277.0002)	(1.3292)	(547.8215)
	46.5299	0.0220	0.0379	0.0000	0.0000	0.4240	0.0000	0.0000	0.0000	0.0930	0.0049
Financial Literacy Score	0.3578***	0.5865***	0.6689***	0.6996***	1.2017***	0.1375	0.8486*	0.3393	0.5078**	0.0754	-0.3181*
	(0.1078)	(0.1323)	(0.1692)	(0.1919)	(0.2992)	(0.1174)	(0.4070)	(0.2384)	(0.1646)	(0.2074)	(0.1279)
	1.4302	1.7977	1.9521	2.0129	3.3258	1.1474	2.3363	1.4040	1.6617	1.0783	0.7275
Age (Linear Term)	0.1839	0.7986**	1.1874***	1.9345***	-2.0988**	1.3218***	0.5908	0.2432	-0.8652*	-0.3792	-0.6343
	(0.3180)	(0.2856)	(0.3392)	(0.3959)	(0.6409)	(0.3058)	(0.5165)	(0.4799)	(0.3979)	(0.4333)	(0.4094)
	1.2018	2.2223	3.2787	6.9205	0.1226	3.7501	1.8055	1.2753	0.4210	0.6844	0.5303
Age (Quadratic Term)	-0.0605	-0.0415	0.3707	0.1704	-1.2728*	-1.1702***	0.0939	-0.5424	-1.0001**	0.4076	0.9503*
	(0.3023)	(0.2746)	(0.3246)	(0.3712)	(0.5533)	(0.2755)	(0.5056)	(0.4423)	(0.3568)	(0.4760)	(0.4530)
	0.9413	0.9594	1.4488	1.1858	0.2801	0.3103	1.0985	0.5813	0.3678	1.5032	2.5866
Age (Cubic Term)	0.0821	-0.4515	-0.6941*	-1.0513**	0.1164	-0.2227	0.0971	0.6839	-0.7185*	0.4240	0.4984
	(0.3146)	(0.2848)	(0.3422)	(0.3949)	(0.4819)	(0.2595)	(0.5338)	(0.4305)	(0.3236)	(0.5164)	(0.5188)
	1.0856	0.6367	0.4995	0.3495	1.1235	0.8003	1.1019	1.9817	0.4875	1.5281	1.6462
Male	-0.2123	0.8374***	0.4918	0.7085*	2.1873***	-0.0571	1.6736*	0.6238	1.5277***	0.3827	-0.8066*
	(0.2817)	(0.2516)	(0.3017)	(0.3441)	(0.4555)	(0.2884)	(0.6610)	(0.4612)	(0.3177)	(0.4444)	(0.3826)
	0.8087	2.3104	1.6352	2.0309	8.9107	0.9445	5.3312	1.8661	4.6077	1.4662	0.4464
Education (Linear Term)	9.8024	0.1581	1.1578^	0.8269	-11.6648	0.4940	0.6858	0.9836	-0.5733	0.7490	-10.4408
	(573.2435)	(0.6128)	(0.6681)	(0.6890)	(1465.5632)	(0.5921)	(1.1073)	(1.0487)	(0.8279)	(0.8670)	(1469.9560)
	18077.3455	1.1713	3.1830	2.2862	0.0000	1.6388	1.9853	2.6740	0.5636	2.1150	0.0000
Education (Quadratic Term)	7.4903	0.2735	-0.6156	0.7274	-8.5999	0.2045	-0.5237	-1.0978	-0.4059	0.1984	-7.7904
	(427.2705)	(0.4644)	(0.5065)	(0.5240)	(1092.3663)	(0.4490)	(0.8394)	(0.7845)	(0.6287)	(0.6550)	(1095.6405)
	1790.6756	1.3146	0.5403	2.0696	0.0002	1.2269	0.5923	0.3336	0.6664	1.2194	0.0004
Education (Cubic Term)	3.2225	-0.1446	-0.0306	0.0940	-3.8939	-0.0146	0.1469	0.1116	-0.3259	-0.2250	-3.1985
	(191.0812)	(0.2665)	(0.2940)	(0.3225)	(488.5211)	(0.2742)	(0.4769)	(0.4402)	(0.3395)	(0.4086)	(489.9854)
	25.0915	0.8654	0.9698	1.0985	0.0204	0.9855	1.1582	1.1180	0.7219	0.7985	0.0408
Finance Job	1.3094	1.2806	-0.3051	15.1510	16.1559	-0.2354	14.9382	14.8541	15.0976	-0.0654	-15.1375
	(1.1332)	(1.1628)	(0.9976)	(793.5142)	(1970.4549)	(0.9887)	(2149.2097)	(1334.6812)	(1277.0001)	(1.2520)	(1002.7931)
	3.7038	3.5987	0.7371	3802025.1204	10384940	0.7902	3072956.5546	2825244.8852	3604057.6777	0.9367	0.0000
Non-Finance Job	0.2407	0.6965	-0.9321	14.1619	14.6688	-0.0679	14.0010	14.0096	15.5007	-0.5533	0.2702
	(0.8616)	(1.1068)	(0.9343)	(793.5141)	(1970.4548)	(0.9131)	(2149.2097)	(1334.6812)	(1277.0001)	(1.1591)	(1.1387)
	1.2722	2.0068	0.3937	1413987.2146	2347374	0.9343	1203792.4577	1214178.7276	5393262.6170	0.5750	1.3102
Finance Student	-0.4991	1.1906	-1.7149^	13.6521	15.2850	-1.5774	13.9015	13.1979	15.4497	-1.1238	0.6880
	(0.9040)	(1.1357)	(0.9856)	(793.5143)	(1970.4548)	(1.1021)	(2149.2097)	(1334.6813)	(1277.0001)	(1.2361)	(1.1913)
	0.6070	3.2890	0.1800	849282.4774	4347201	0.2065	1089759.7095	539228.3726	5125355.5021	0.3250	1.9898
Non-Finance Student	-0.9529	0.1164	-1.0736	14.0317	15.1331	-1.1574	13.4735	14.3610	15.0615	-2.1317	1.4574
	(0.8931)	(1.1715)	(1.0206)	(793.5144)	(1970.4548)	(1.0915)	(2149.2099)	(1334.6813)	(1277.0001)	(1.4974)	(1.1565)
	0.3856	1.1235	0.3418	1241373.7511	3734265	0.3143	710336.3402	1725464.1152	3476438.1457	0.1186	4.2949
Retired	-1.3344	0.9001	-0.2177	12.9703	1.8580	0.3103	-0.8422	-0.1291	0.9681	0.0139	-0.0476
	-1.0875	-1.312	-1.2107	-793.5149	(2601.7328)	-1.1056	-2798.7854	(1749.8582)	(1677.3083)	(1.6167)	(1.5897)
	0.2633	2.4598	0.8043	429462.643	6.4107	1.3639	0.4307	0.8789	2.6328	1.0140	0.9535
McFadden R²	0.1005	0.176	0.2083	0.2644	0.4374	0.2097	0.2596	0.173	0.2161	0.0611	0.1758

Note. Coefficients are reported with statistical significance indicated by asterisks. Standard errors are shown in parentheses. Odds ratios are also reported to facilitate explanation.

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

<u>Savings Instruments</u>

In the model predicting whether individuals invest in savings instruments, McFadden R^2 was 0.1005. Although this indicates modest explanatory power, explaining 10% of the variation, it remains within an acceptable range for behavioral research, where lower fit statistics are common (Gupta et al., 2024).

Financial literacy was positively and significantly associated with the likelihood of investing in savings instruments. Specifically, each one-unit increase in financial literacy was associated with a 1.43-fold increase in the odds of investing in savings instruments, controlling for demographic characteristics.

None of the control variables, including age, gender, education, and occupation, exhibited statistically significant effects on savings instrument investment decisions.

Stocks

The analysis focused on stock investment behavior yielded a McFadden R^2 of 0.176. This result indicates that the model captured around 17.6% of the variance in outcomes, aligning with a moderate level of predictive adequacy based on McFadden's thresholds.

Financial literacy demonstrated a positive and statistically significant relationship with stock investment. Specifically, each one-unit increase in financial literacy was associated with 1.80 times higher odds of investing in stocks, controlling for demographic factors.

In terms of control variables, age exhibited a significant positive linear effect, with each one-unit increase in age group associated with a 2.22-fold increase in the odds of investing in stocks. The quadratic and cubic age terms were not statistically significant, indicating no evidence of non-linear effects. Gender was also a significant predictor, with men demonstrating 2.31 times greater odds of investing in stocks compared to women. Education level and occupation category variables were not significantly associated with stock investment decisions.

Bonds

The model assessing decisions related to bond investments produced a McFadden R^2 of 0.2083. This means that about 20.8% of the variation in bond-related behavior was explained, pointing to a fairly strong fit under commonly accepted logistic regression benchmarks.

Financial literacy was positively and significantly associated with bond investment. Each one-unit increase in financial literacy corresponded to a 1.95-fold increase in the odds of investing in bonds, after controlling for demographic variables.

In terms of control variables, age exhibited a significant nonlinear effect, characterized by a positive linear term but a negative cubic term, suggesting the presence of an inflection point where the direction of the effect changes across the age spectrum. Gender was not a significant predictor. Education demonstrated a marginally significant positive linear effect, indicating a slight tendency for higher education levels to be associated with bond investment. Occupation categories were generally non-significant, although finance students showed a marginally significant negative association with bond investment behavior.

Mutual Funds

When predicting mutual fund investment behavior, the model achieved a McFadden R^2 of 0.2644. Explaining roughly 26.5% of the variance, this indicates a strong and reliable model fit per McFadden's guidance on interpreting pseudo R-squared values.

Financial literacy was positively and significantly associated with mutual fund investment. Each one-unit increase in financial literacy was linked to a 2.01-fold increase in the odds of investing in mutual funds, controlling for demographic variables.

In terms of control variables, age exhibited a significant nonlinear effect, characterized by a positive linear term but a negative cubic term, suggesting the presence of an inflection point where the direction of the effect changes across the age spectrum. Gender was also a significant predictor, with men showing 2.03 times greater odds of investing in mutual funds compared to women. Education variables were not significantly associated with mutual fund investment decisions, and occupation categories likewise showed no significant effects.

Exchange-Traded Funds (ETFs)

The regression analyzing ETF investment decisions yielded a McFadden R^2 of 0.4374, reflecting a particularly robust model. With approximately 44% of the behavior variance explained, the fit is well above the threshold for a strong predictive relationship.

Financial literacy was positively and significantly associated with ETF investment. Each one-unit increase in financial literacy corresponded to a 3.33-fold increase in the odds of investing in ETFs, after controlling for demographic characteristics.

In terms of control variables, age exhibited a significant nonlinear effect, with negative linear and quadratic terms, indicating a progressively steeper decline in ETF investment as age increases. Gender was also a significant predictor, with men exhibiting approximately 9 times greater odds of investing in ETFs compared to women. Education level and occupation category variables were not significantly associated with ETF investment decisions.

Real Estate

The model examining real estate investment choices resulted in a McFadden R^2 of 0.2097. This suggests that just under 21% of the decision-making variance was accounted for, reflecting a solid level of model performance.

Financial literacy had a positive but not statistically significant coefficient, indicating no clear relationship between financial literacy and real estate investment when controlling for demographic factors.

In terms of control variables, age exhibited a significant nonlinear relationship with real estate investment, characterized by a positive linear term and a negative quadratic term, peaking at middle age, and then declining as individuals grow older, forming an inverted U-shaped curve. Gender, education level, and occupation categories were not significantly associated with real estate investment decisions.

Derivatives

For derivative investment behaviors, the regression model reported a McFadden R^2 of 0.2596. Explaining about 26% of the variance, the model demonstrates a strong level of predictive power based on standard guidelines.

Financial literacy was positively and significantly associated with derivative investment. Each one-unit increase in financial literacy was linked to a 2.34-fold increase in the odds of investing in derivatives, controlling for demographic variables.

In terms of control variables, none of the age terms were statistically significant, indicating no clear linear, quadratic, or cubic relationship between age and derivative investment. Gender was a significant predictor, with men exhibiting 5.33 times greater odds of investing in derivatives compared to women. Education variables were not significantly associated with derivative investment decisions, nor were occupation categories.

Commodities

The analysis of commodity investment decisions returned a McFadden R^2 of 0.1730. This value implies the model captured 17.3% of the variance, which is considered a moderately good fit for behavioral data.

Financial literacy had a positive but not statistically significant coefficient, indicating no clear relationship between financial literacy and commodities investment when controlling for demographic factors.

None of the control variables, including age, gender, education, and occupation, exhibited statistically significant effects on commodities investment decisions.

Cryptocurrency

The regression model aimed at predicting cryptocurrency investments achieved a McFadden R^2 of 0.2161. This indicates that roughly 22% of the variance was accounted for, supporting the model's adequacy in explaining such financial behavior.

Financial literacy was positively and significantly associated with cryptocurrency investment. Each one-unit increase in financial literacy corresponded to a 1.66-fold increase in the odds of investing in cryptocurrencies, after controlling for demographic factors.

In terms of control variables, age exhibited a significant negative relationship with cryptocurrency investment, characterized by negative linear, quadratic, and cubic terms. Gender was also a significant predictor, with men exhibiting 4.61 times greater odds of investing in cryptocurrencies compared to women. Education level and occupation category variables were not significantly associated with cryptocurrency investment decisions.

Collectibles

Investment in collectibles was modeled with a McFadden R^2 of 0.0611. While this relatively low value reflects limited explanatory power (about 6%), it remains within acceptable bounds for models in social science domains where behavior is inherently complex (Gupta et al., 2024).

Financial literacy had a positive but not statistically significant coefficient, indicating no clear relationship between financial literacy and collectibles investment when controlling for demographic factors.

None of the control variables, including age, gender, education, and occupation, exhibited statistically significant effects on commodities investment decisions.

No Investment

When it came to predicting the likelihood of not investing, the model yielded a McFadden R^2 of 0.1758. This means the model explains approximately 17.6% of the variance in non-investment decisions, suggesting a moderate but acceptable level of fit.

Financial literacy had a negative and significant coefficient. For each one-unit increase in financial literacy, the odds of choosing not to invest were 0.73 times as likely, representing a 27% decrease in the odds of choosing not to invest, controlling for demographic variables.

In terms of control variables, age exhibited a significant positive quadratic relationship, suggesting a U-shaped association with the likelihood of not investing. The linear and cubic terms were insignificant. Gender was a significant predictor, with men showing 2.24 times greater odds of investing than women. Education variables were not significantly associated with the decision of not investing, nor were occupation categories.

4.2.2.2. Active versus Passive Investment Strategy

Table 4.3: Impact of Financial Literacy on Active versus Passive Investment Strategy

	Coefficient	Standard Error	Odds Ratio
(Intercept)	-2.0000*	(1.0178)	0.1353
Financial Literacy Score	0.2796^	(0.1470)	1.3226
Age (Linear Term)	0.2804	(0.3067)	1.3236
Age (Quadratic Term)	0.1309	(0.3111)	1.1399
Age (Cubic Term)	-0.6994*	(0.3263)	0.4969
Male	0.3348	(0.2986)	1.3977
Education (Linear Term)	0.3019	(0.6464)	1.3525
Education (Quadratic Term)	0.0335	(0.4931)	1.0341
Education (Cubic Term)	-0.1562	(0.2902)	0.8554
Finance Job	-0.4462	(0.9570)	0.6401
Non-Finance Job	-0.3849	(0.8840)	0.6805
Finance Student	-0.6222	(0.9345)	0.5368
Non-Finance Student	-1.9426^	(1.1360)	0.1433
Retired	0.3011	(1.1517)	1.3513
McFadden R^2	0.0597		

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

The model evaluating preference for active versus passive investment strategies showed a McFadden R^2 of 0.0597. Although modest, explaining 6% of the variance, such results are still meaningful in the context of behavioral analysis, where high explanatory power is rarely achieved (Gupta et al., 2024).

Financial literacy exhibited a positive effect on the likelihood of choosing an active investment strategy. However, the effect was only marginally significant, with each one-unit increase in financial literacy associated with a 1.32-fold increase in the odds of choosing active strategies, controlling for demographic variables.

In terms of control variables, age demonstrated a significant negative cubic relationship with the decision to choose an active investment strategy, suggesting that the relationship is nonlinear with one or more inflection points. The linear and quadratic terms were not significant. Gender was positively associated with active investing, but the relationship was not statistically significant. Education level variables were not significantly related to investment strategy choice. Occupation categories did not show significant effects, although non-finance students exhibited a marginally significant negative tendency toward active investing.

4.2.2.3. Investment Horizon Preferences

Table 4.4: Impact of Financial Literacy on Investment Horizon Preferences

	Coefficient	Standard Error
Financial Literacy Score	0.0562	(0.0586)
Age (Linear Term)	0.1914	(0.1472)
Age (Quadratic Term)	-0.0195	(0.1416)
Age (Cubic Term)	0.1167	(0.1429)
Male	0.0354	(0.1384)
Education (Linear Term)	-0.1120	(0.3266)
Education (Quadratic Term)	-0.1689	(0.2473)
Education (Cubic Term)	-0.1626	(0.1427)
Finance Job	0.4411	(0.4936)
Non-Finance Job	-0.0163	(0.4472)
Finance Student	0.0082	(0.4701)
Non-Finance Student	0.1246	(0.4772)
Retired	-0.6624	(0.5684)
short term|medium term	-1.1804*	(0.4948)
medium term|long term	0.2187	(0.4903)
McFadden R^2	0.0241	

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

The regression predicting preference for long-term strategies over short-term trading produced a McFadden R^2 of just 0.0241. This reflects weak predictive strength, likely attributable to the nuanced and individual nature of strategic financial planning (Gupta et al., 2024).

Financial literacy had a positive but not statistically significant coefficient, indicating no clear relationship between financial literacy and the preference for a long-term investment strategy when controlling for demographic factors.

None of the control variables, including age, gender, education, and occupation, exhibited statistically significant effects on the preference for a long-term investment strategy.

Threshold parameters define the boundaries between investment horizon categories, while holding all other predictor variables constant. Intercept "short-term|medium-term" was significantly negative, suggesting a lower likelihood of choosing a medium-term over a short-term strategy. In contrast, intercept "medium-term|long-term" was not significant, indicating no substantial difference in the likelihood of choosing medium-term over long-term strategies.

4.2.2.4. Risk Tolerance

Table 4.5: Impact of Financial Literacy on Risk Tolerance

	Coefficient	Standard Error	Odds Ratio
Financial Literacy Score	0.1548^	(0.0833)	1.1674
Age (Linear Term)	-0.7977***	(0.2198)	0.4504
Age (Quadratic Term)	0.1574	(0.2105)	1.1705
Age (Cubic Term)	-0.3142	(0.2180)	0.7304
Male	1.0534***	(0.2099)	2.8673
Education (Linear Term)	0.3339	(0.4861)	1.3965
Education (Quadratic Term)	0.0960	(0.3676)	1.1008
Education (Cubic Term)	-0.0537	(0.2094)	0.9477
Finance Job	1.1848	(0.7874)	3.2702
Non-Finance Job	0.4699	(0.7230)	1.5999
Finance Student	0.4189	(0.7434)	1.5202
Non-Finance Student	0.2181	(0.7468)	1.2437
Retired	1.0373	(0.9433)	2.8216
Very risk-averse|Somewhat risk-averse	-0.1051	(0.7781)	—
Somewhat risk-averse|Neutral	1.3766^	(0.7791)	—
Neutral|Somewhat risk-tolerant	2.8689***	(0.7887)	—
Somewhat risk-tolerant|Very risk-tolerant	5.0168***	(0.8228)	—
McFadden R²	0.0746		

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

The model assessing risk tolerance returned a McFadden R^2 of 0.0746. Although this accounts for only 7.46% of the variance, such a figure is not unusual for studies involving psychological traits like risk tolerance (Gupta et al., 2024).

Financial literacy exhibited a positive effect on risk tolerance. However, the effect was only marginally significant, with each one-unit increase in financial literacy associated with a 1.17-fold increase in the odds of being more risk tolerant, controlling for demographic variables.

In terms of control variables, age exhibited a significant negative linear effect on risk tolerance. For each one-unit increase in age group, the odds of having a higher risk tolerance were 0.45 times as likely, meaning the odds decrease by 55%, controlling for other variables. The quadratic and cubic terms for age were not significant, suggesting a linear relationship. Gender was a significant predictor, with men having 2.87 times greater odds of being more risk-tolerant compared to women. Education variables did not significantly influence risk tolerance, nor did occupation categories.

Threshold parameters define the boundaries between different risk tolerance categories, while holding all other predictors constant. Intercept "very risk-averse|somewhat risk-averse" was not significant, suggesting no clear boundary between these two categories. On the other hand, intercept "somewhat risk-averse|neutral" was marginally significant, indicating a weak but noteworthy threshold between these two levels. Furthermore, intercepts "neutral|somewhat risk-tolerant" and "somewhat risk-tolerant|very risk-tolerant" had significantly positive thresholds, indicating that as financial literacy increases, individuals are more likely to move to higher levels of risk tolerance.

4.2.2.5. Trading Frequency

Table 4.6: Impact of Financial Literacy on Trading Frequency

	Coefficient	Standard Error
Financial Literacy Score	0.1435**	(0.0522)
Age (Linear Term)	0.0988	(0.1295)
Age (Quadratic Term)	-0.0421	(0.1265)
Age (Cubic Term)	-0.2020	(0.1307)
Male	0.7066***	(0.1242)
Education (Linear Term)	-0.0797	(0.2957)
Education (Quadratic Term)	0.2013	(0.2241)
Education (Cubic Term)	-0.0725	(0.1277)
Finance Job	0.0598	(0.4425)
Non-Finance Job	0.0435	(0.4066)
Finance Student	0.1514	(0.4275)
Non-Finance Student	-0.1202	(0.4298)
Retired	-0.1430	(0.5306)
never|rarely	0.4075	(0.4410)
rarely|annually	1.4322**	(0.4457)
annually|monthly	1.481***	(0.4460)
monthly|weekly	2.3803***	(0.4530)
weekly|daily	2.8668***	(0.4589)
McFadden R^2	0.0659	

*Significance levels: ***p ≤ 0.001, **p ≤ 0.01, *p ≤ 0.05, ^p ≤ .1*

Source: Own analysis

The regression model predicting how often individuals engage in trading activity had a McFadden R^2 of 0.0659. This suggests that approximately 6.6% of the variance in trading frequency is explained by the model, a modest fit but one that still offers insights in the context of human behavior modeling (Gupta et al., 2024).

Financial literacy was positively and significantly associated with trading frequency, after controlling for demographic factors.

In terms of control variables, only gender was a significant predictor of trading frequency, with men investing more frequently than women. Other variables, including age, education, and occupation categories, did not statistically influence trading frequency.

Threshold parameters define the boundaries between different investment frequency categories, estimated while holding all other predictor variables constant. All intercepts, except for the intercept "never|rarely", showed statistically significant positive thresholds. This suggests that as financial literacy increases, individuals are more likely to move to higher investment frequency categories, with the exception of the intercept "never|rarely".

5. Discussion

This chapter interprets the study's key findings through the framework of six core hypotheses, each addressing a specific aspect of the relationship between demographic characteristics, financial literacy, and investment behavior. The discussion critically evaluates these results in relation to existing empirical literature, highlighting areas of alignment and divergence. In doing so, it assesses the extent to which demographic factors influence financial literacy and how that literacy, in turn, shapes investment decisions. The chapter also considers the broader practical implications of these findings for financial education policy in Belgium. Finally, it acknowledges the study's limitations and outlines recommendations for future research to further explore this multifaceted relationship.

5.1. Key Findings and Interpretation

Each of the following hypotheses is examined in relation to both the empirical results of the study and the broader academic literature, ensuring that interpretations are contextualized within the existing body of knowledge. Where relevant, inconsistencies, complexities, and potential moderating influences are acknowledged.

- H1: Demographics significantly influence financial literacy.

  - H1a: Age significantly influences financial literacy, with younger individuals generally exhibiting lower levels of financial knowledge, which gradually increases in middle adulthood but declines in later years.

The empirical analysis did not find age to be a statistically significant predictor of financial literacy. As such, Hypothesis H1a is not supported by the data.

This result contrasts with traditional life-cycle models, which propose an inverted U-shaped relationship between age and financial literacy—characterized by limited knowledge in youth, peak proficiency in middle adulthood, and decline in older age due to cognitive aging (Agarwal et al., 2009; Henager & Cude, 2016; Lusardi & Mitchell, 2014; Méndez Prado et al., 2022). However, recent literature complicates this narrative. Some studies suggest that older individuals may mitigate cognitive decline through the use of professional financial advice (Kim et al., 2021), and, in the Belgian context, older adults (55+) have been shown to score higher on financial literacy assessments than their younger counterparts (Demertzis et al., 2024). Moreover, Deloitte Belgium (2023) reports greater financial resilience among individuals aged 18–34 compared to those aged 35–54, indicating that generational shifts in financial awareness and technology adoption may be altering traditional age-related trends.

Consequently, the absence of a clear statistical relationship in this study underscores the complexity of the age-financial literacy dynamic and cannot decisively identify a singular pattern in the Belgian context.

  - H1b: Gender significantly influences financial literacy, with men typically exhibiting higher levels of financial literacy compared to women.

The findings provide robust support for Hypothesis H1b. Men demonstrated significantly higher financial literacy than women, with the odds of belonging to a higher financial literacy category being approximately 4.5 times greater than for women.

This result aligns with a well-documented body of research that identifies persistent gender gaps in financial literacy, both globally and within Belgium (Demertzis et al., 2024; Lusardi & Mitchell, 2011, 2014). Importantly, these disparities are not solely attributable to knowledge differences. Behavioral finance literature suggests that cognitive biases also contribute. For instance, loss aversion—a tendency more pronounced in women—may influence how financial knowledge is internalized and applied, potentially constraining risk-taking and financial engagement (Barber & Odean, 2001; Bihari et al., 2022).

Thus, while the gender gap in financial literacy is statistically evident, its underlying causes are likely multifactorial, involving both informational and behavioral components.

- H1c: Socio-Economic Status (SES) positively influences financial literacy, such that individuals with higher SES—measured in terms of income, education, and occupational prestige—tend to possess superior financial knowledge.

The results offer partial support for Hypothesis H1c.

Due to multicollinearity, income was excluded from the regression models, precluding an empirical test of its effect. Consequently, no conclusions can be drawn regarding the income-financial literacy relationship in this study. This limitation stands in contrast to prior findings, which consistently report a positive correlation between income and financial literacy (Deloitte Belgium, 2023; Demertzis et al., 2024; Nursjanti & Amaliawiati, 2024).

In contrast, education emerged as a statistically significant predictor of financial literacy. Each additional unit of educational attainment was associated with 5.91 times greater odds of belonging to a higher financial literacy category, with a linear relationship observed. This outcome corroborates extensive research identifying education as a foundational driver of financial knowledge and decision-making competence (Demertzis et al., 2024; Hastings & Mitchell, 2011; Lusardi & Mitchell, 2014).

Occupation also played a notable, though selective, role. Individuals employed in finance-related professions and students in finance fields exhibited significantly higher levels of financial literacy compared to the unemployed. However, no significant effects were observed for individuals in non-finance professions or retirees, suggesting that domain-specific exposure rather than general employment status contributes to financial capability. These findings are partially consistent with the notion that economic engagement enhances financial acumen, though such benefits appear contingent on the nature of the occupation (Nursjanti & Amaliawiati, 2024; OECD, 2023).

In summary, while income effects could not be assessed, the positive influence of education and finance-specific employment supports Hypothesis H1c in part.

- H2: Greater financial literacy positively influences asset allocation and portfolio diversification.

The empirical evidence strongly supports Hypothesis H2, indicating that financial literacy significantly enhances investment activity and diversification across multiple asset classes, with a few notable exceptions.

Financial literacy was positively and significantly associated with investment in a broad range of asset categories. Most notably, a one-unit increase in financial literacy increased the likelihood of investing in ETFs by 3.33 times, followed by derivatives (2.34x), mutual funds (2.01x), bonds (1.95x), stocks (1.80x), cryptocurrencies (1.66x), and savings instruments (1.43x). These findings suggest that financially literate individuals are more likely to engage in diversified asset classes.

Conversely, no significant relationship was found between financial literacy and investment in real estate, commodities, or collectibles. Importantly, a negative association was observed between financial literacy and the probability of having no investments at all, indicating that increased financial literacy reduces financial market disengagement.

These results reinforce prior research demonstrating that financial literacy improves individuals' capacity to diversify portfolios, assess risk-return trade-offs, and make informed asset allocation decisions (De Winne & Petkeviciute, 2021; Yang et al., 2022).

Control variables yielded further insights. Age exhibited nonlinear effects across asset classes: investments in bonds and mutual funds rose steeply in early adulthood, plateaued in middle age, and declined thereafter. The relationship between age and real estate investment followed an inverted U-shape, increasing until middle age and then declining, while the likelihood of holding no investments exhibited a classic U-shape, peaking among both younger and older adults and reaching its lowest point in middle age. ETF investments declined at an accelerating rate with age, with the steepest decreases occurring in later life, while cryptocurrency participation decreased sharply with advancing age. Notably, older individuals demonstrated a higher propensity for stock investments.

Gender effects were particularly pronounced. Men were significantly more likely than women to invest across many asset classes, including stocks, mutual funds, ETFs, derivatives, and cryptocurrencies. They were also significantly less likely to hold no investments. These results are in line with literature highlighting men's higher stock market participation, while women tend to exhibit lower stock market engagement (Van Rooij et al., 2012).

In sum, Hypothesis H2 receives strong empirical support. Financial literacy appears to facilitate broader and more diversified investment behavior, while demographic factors such as age and gender significantly shape these patterns.

- H3: Higher levels of financial literacy are positively associated with the likelihood of engaging in active investment strategies over passive ones.

The findings reveal a positive, albeit marginally significant, association between financial literacy and active investment strategy preference. Specifically, a one-unit increase in financial literacy was associated with a 1.32-fold increase in the likelihood of adopting an active investment strategy. While this trend supports the direction of Hypothesis H3, the marginal significance prevents conclusive confirmation.

This observed pattern is broadly consistent with existing literature, which suggests that financial literacy enhances investors' skills to analyze financial information and manage investments actively (Okicic & Selimović, 2020; Van Rooij et al., 2012). Financially knowledgeable individuals are more likely to make informed strategic decisions, potentially enhancing portfolio performance.

Control variable analysis further deepens this understanding. Age exerted a significant nonlinear influence on strategy preference, with active investment rising in early adulthood, plateauing during midlife and declining in older age. This pattern is coherent with the life-cycle hypothesis, which posits a decrease in cognitive flexibility and information processing with age (Agarwal et al., 2009), reducing the likelihood of older adults favoring active portfolio management.

Although the evidence does not fully validate Hypothesis H3, it points toward a meaningful role for financial literacy in promoting active investment behavior. Future research with larger sample sizes may uncover more robust statistical relationships.

- H4: Individuals with greater levels of financial literacy are more likely to adopt long-term investment strategies rather than short-term trading.

Contrary to expectations, the study did not find a statistically significant relationship between financial literacy and long-term investment orientation. Consequently, Hypothesis H4 is not supported by the empirical data.

The lack of significance challenges prevailing assumptions in the literature, which suggest that financial literacy promotes an understanding of long-term investment benefits—such as market cycles, compounding interest, and risk management (Batra, 2024). Financially literate investors are typically characterized as more patient, an attribute that is theoretically aligned with long-term investing (Aman et al., 2024).

However, an alternative emerging explanation suggests that high financial literacy may also be associated with overconfidence, particularly among certain demographic groups (Barber & Odean, 2001). This overconfidence could manifest as a preference for more frequent trading, even when long-term strategies are objectively superior (Aman et al., 2024). Therefore, the absence of a significant effect may reflect this dual nature of financial literacy: while it can promote sound investment principles, it may also embolden risk-taking behavior that diverges from long-term planning.

These findings point to a more nuanced understanding of investor psychology, wherein financial literacy does not necessarily translate into long-termism, and may, under specific conditions, encourage more speculative behavior.

- H5: Higher financial literacy is positively correlated with higher risk tolerance.

The findings suggest a positive yet only marginally significant relationship between financial literacy and risk tolerance. Each unit increase in financial literacy was associated with a 1.17-fold increase in the odds of being more risk-tolerant. While this trend is directionally aligned with Hypothesis H5, the effect does not reach conventional levels of statistical significance.

This tentative association is consistent with theoretical expectations. Financial literacy equips individuals with the tools to understand and evaluate risk more effectively, thereby reducing irrational fear of market volatility and fostering a higher tolerance for risk (Aeknarajindawat, 2020). In contrast, lower financial literacy often correlates with excessive risk aversion, driven more by skepticism and cognitive limitations toward financial markets than by rational assessments of volatility (Bucher-Koenen & Ziegelmeyer, 2011).

The moderating effects of control variables further clarify this dynamic. Age was inversely related to risk tolerance, with older individuals exhibiting significantly lower risk preferences, a finding consistent with cognitive aging theories (Agarwal et al., 2009). Gender also emerged as a significant factor, with men demonstrating greater risk tolerance than women. This aligns with established research suggesting that men, on average, engage in riskier financial behavior, whereas women tend to adopt more conservative strategies, potentially contributing to better long-term outcomes (Barber & Odean, 2001; Bihari et al., 2022; Hariharan et al., 2000; Van Rooij et al., 2012).

In sum, while Hypothesis H5 cannot be confirmed with statistical certainty, the observed patterns mirror broader empirical trends, highlighting the complex interplay between financial literacy, risk tolerance, and demographic characteristics.

– H6: Greater levels of financial literacy are associated with lower trading frequency, avoiding excessive trading.

Contrary to the hypothesis, the study found a statistically significant positive relationship between financial literacy and trading frequency. Thus, rather than discouraging frequent trading, higher financial literacy was associated with increased trading activity. Hypothesis H6 is thus not supported.

This result challenges the conventional view that financial literacy fosters disciplined, more stable long-term investing and deters impulsive or speculative behaviors (Aman et al., 2024; Batra, 2024). Nevertheless, the present findings may reflect a phenomenon documented by Barber and Odean (2001), wherein increased knowledge and perceived expertise contribute to overconfidence, particularly among male investors, resulting in higher trading frequency despite potential negative effects on returns. The gender analysis in this study further substantiates this explanation: men traded significantly more frequently than women, consistent with the overconfidence hypothesis.

Therefore, while financial literacy enhances investment participation and market engagement, it may simultaneously foster behaviors, such as frequent trading, that are not always optimal from a return-maximization perspective.

5.2. Practical Implications

The findings of this study offer valuable insights for the development and refinement of financial education programs in Belgium, with several key implications emerging from the analysis.

Although age and income were not found to be statistically significant predictors in the final model, the results nonetheless highlight the importance of targeting financial literacy initiatives toward specific demographic groups. In particular, women, individuals with lower levels of educational attainment, and those with lower occupational status, including the unemployed, emerged as populations warranting focused attention. These groups are often disproportionately affected by restricted access to financial knowledge and may face structural constraints that limit their capacity for informed financial decision-making. Therefore, educational content aimed at these audiences should be designed to be inclusive, comprehensible, and practically oriented. Employing simplified language may prove especially effective in engaging individuals with limited formal education and enhancing their financial comprehension.

Furthermore, the growing body of evidence linking early financial education to improved long-term financial outcomes (Bernheim et al., 2001) underscores the urgency of integrating financial literacy into the formal education system. Policymakers are encouraged to consider the introduction of mandatory financial literacy curricula at the secondary school level. Such integration would equip young individuals with foundational knowledge in core areas such as saving behavior, compound interest, and portfolio diversification—skills that are essential for navigating increasingly complex financial environments upon entering adulthood.

In addition to foundational concepts, financial education interventions should emphasize the development of competent investment practices. Central to this is fostering the ability to evaluate risk appropriately, understand the merits of diversification, and adopt a long-term perspective on wealth accumulation. Importantly, educational efforts should also caution against the pitfalls of active investment strategies and excessive trading, which may stem from overconfidence or speculative inclinations rather than rational analysis. As such, it is imperative that financial literacy interventions move beyond the mere transmission of technical knowledge. They should also aim to mitigate behavioral biases, such as risk aversion and overconfidence, that can significantly distort financial decision-making.

In a nutshell, effective financial education should be both inclusive and comprehensive, addressing not only informational deficits but also the psychological and structural factors that shape individual financial behavior. Tailored, behaviorally-informed interventions may therefore represent a critical step toward enhancing financial well-being across diverse segments of the Belgian population.

5.3. Research Limitations

Several limitations must be considered when interpreting the findings of this study, each of which may influence the robustness and generalizability of the results.

To begin with, as outlined in the methodology section, the sampling strategy presents inherent limitations. The reliance on self-selection may have introduced self-selection bias, whereby individuals who chose to participate in the survey could possess specific traits or interests not representative of the broader Belgian population. Furthermore, the use of a snowball sampling technique, while effective in extending participant reach, may have exacerbated homogeneity within the sample, thereby increasing the risk of sampling bias.

Secondly, the demographic sample was skewed toward younger individuals, particularly those aged 18 to 24, and included a disproportionate number of participants with higher educational attainment. As a result, the findings may not be generalizable to older adults or individuals with lower levels of formal education. While there was some variation in gender and occupation, the overrepresentation of participants from non-finance-related professions and the underrepresentation of other occupational categories may have shaped the observed relationships between financial literacy and investment behavior.

A third limitation concerns certain investment categories—such as hedge funds, private equity, and venture capital—which had insufficient representation within the sample, precluding robust statistical analysis of these specific behaviors. Even among more common asset classes, including mutual funds, ETFs, derivatives, commodities, cryptocurrencies, and cases of non-investment, small subsample sizes occasionally led to inflated standard errors, thereby diminishing the statistical power and precision of regression estimates. Additionally, imbalances in response patterns within individual investment behavior items—specifically, the overrepresentation of certain behaviors and the underrepresentation of others within the same question—may have biased the observed relationships between financial literacy and investment decisions, further limiting the robustness of the findings.

Further, the assessment of financial literacy was based on a relatively narrow set of indicators—namely, three items developed by Lusardi and Mitchell supplemented by two additional questions—which may not comprehensively reflect the full spectrum of financial knowledge and capabilities. Moreover, several critical variables were measured using self-reported ordinal scales. These are inherently vulnerable to social desirability bias, as well as potential misinterpretation by respondents, thereby limiting the precision and validity of the data.

Given these measurement constraints, the overall financial literacy scores within the sample were relatively high, raising concerns about the overrepresentation of financially literate individuals. This phenomenon may limit the applicability of the findings to the general population, particularly among groups with lower financial literacy.

Lastly, the regression models were constrained by multicollinearity, particularly involving income as a predictor. This statistical complication necessitated the exclusion of income from the final analysis, thereby limiting the extent to which SES could be fully examined as a determinant of financial literacy and investment behavior.

5.4. Future Research Directions

Building upon the findings and acknowledging the limitations of the present study, several avenues for future research are recommended to enhance both the theoretical understanding and practical application of financial literacy.

To begin with, methodological refinements are crucial for improving the generalizability and precision of future research. Employing stratified sampling[16] methods would allow for more representative samples across key demographic strata and investment behaviors, particularly those that were underrepresented in the current study. This would enable more robust and externally valid conclusions.

In addition, the exclusion of income from the regression models due to multicollinearity warrants methodological innovation. Future studies should consider incorporating income as a central socioeconomic variable by applying alternative statistical techniques, such as ridge regression[17], that can address multicollinearity while retaining the variable's interpretive significance. Such approaches would provide a more comprehensive understanding of the socioeconomic determinants of financial literacy and investment behavior.

Moreover, the absence of a significant relationship between age and financial literacy, despite theoretical and empirical expectations, suggests the need for further investigation. Subsequent studies should utilize demographically balanced samples and consider longitudinal designs to better capture age-related patterns and developmental trajectories in financial literacy across the life course.

Furthermore, the marginal or absent associations observed between financial literacy and various investment strategies—including preferences for active versus passive management, levels of risk tolerance, and long-term orientation—indicate that these relationships may be more nuanced than initially presumed. Future research should aim to achieve more balanced sampling across different investor profiles to allow for a more detailed exploration of how financial literacy influences these complex relationships.

Equally important, the findings imply that higher levels of financial literacy do not necessarily translate into optimal financial behavior. This highlights the importance of examining behavioral mediators on financial decision-making. A more integrated behavioral framework could yield deeper insights into the mechanisms that underlie financial choices.

Lastly, in light of the pressing need for effective financial education, future studies should assess the long-term impact of targeted educational interventions. Special attention should be given to vulnerable populations, including women and those with lower educational attainment and occupational status, not only in terms of knowledge acquisition but also in terms of sustained behavioral change. Evaluating the efficacy of such interventions through longitudinal, outcome-based designs would provide critical evidence for policy and program development.

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[16] Stratified sampling is a sampling method that involves dividing a population into distinct subgroups (strata) based on shared characteristics, and then randomly selecting samples from each stratum to ensure proportional representation of all groups (Nikolopoulou, 2022).

[17] Ridge regression is a regression technique that introduces a penalty on large coefficients to prevent overfitting and improve model stability in the presence of multicollinearity (Murel & Kavlakoglu, 2023).

6. Conclusion

This thesis set out to investigate how variations in financial literacy, shaped by demographic factors, influence investment behavior among the Belgian population aged 18 to 65. The findings offer a nuanced and multifaceted response to this central research question, contributing both empirical evidence and theoretical insight to an evolving field of study.

The analysis clearly demonstrates that financial literacy significantly influences individuals' engagement with investment opportunities. Higher levels of financial literacy are strongly associated with greater asset allocation, more diversified portfolios, and a reduced likelihood of complete investment avoidance. These outcomes reinforce the view of financial literacy as a foundational enabler of rational and informed financial behavior. However, the study also reveals more intricate and counterintuitive patterns. Specifically, increased financial literacy is linked to higher trading frequency—a behavior frequently associated with overconfidence. This paradox underscores the dual role of financial literacy: while it equips individuals for more sophisticated market participation, it may also heighten exposure to cognitive biases that compromise long-term financial outcomes.

Further examination of the link between financial literacy and specific investment strategies uncovers additional layers of complexity. Although financial literacy appears to marginally encourage active investment approaches and a higher tolerance for risk, it shows no association with long-term investment behavior. This suggests that financial knowledge alone does not necessarily translate into prudent risk management or sustained, goal-oriented investing—highlighting the need for a broader conceptualization of financial competence beyond mere knowledge acquisition.

Demographic variables serve to further contextualize these findings. Gender and education emerge as consistent and robust predictors of financial literacy, with men and individuals possessing higher educational attainment demonstrating significantly greater financial understanding. In contrast, age does not appear to exert a notable influence, and the role of occupational background remains mixed—only those employed in finance-related sectors exhibit a clear advantage. These disparities indicate that financial literacy is unevenly distributed across the population, reinforcing the importance of targeted educational interventions to bridge persistent knowledge gaps and promote financial inclusivity.

From a methodological perspective, the study employed a quantitative research design centered on regression analysis to test a series of hypotheses. This approach proved effective in uncovering both anticipated trends and emergent patterns. While certain limitations—such as potential biases and the exclusion of income due to multicollinearity—should be acknowledged, the overall methodology was well-suited to the study's objectives. Moreover, the findings not only validated established theoretical models but also highlighted context-specific complexities within the Belgian population that warrant further scholarly attention.

Ultimately, this thesis contributes meaningfully to the literature on financial literacy by addressing a significant empirical gap in the Belgian context and linking literacy directly to observable investment behaviors. It advances current understanding by illustrating both the empowering and potentially adverse effects of financial literacy, while also emphasizing enduring demographic inequalities. These insights carry critical implications for policymakers and educators striving to foster more equitable and effective financial education. By elucidating the pathways through which financial literacy shapes investment decision-making, this research supports the development of targeted, evidence-based strategies aimed at enhancing economic resilience and participation in an increasingly complex financial environment.

7. Appendices

7.1. Appendix 1 – Questionnaire

This appendix contains the full version of the questionnaire used in the study, presented in both English and French. The questionnaire was designed to collect data on respondents' demographics, financial literacy, and investment behavior. It served as the primary data collection tool.

English version

Thank you for participating in this survey. Your responses will help me understand how financial literacy and demographics impact the investment behavior of individuals aged 18 to 65.

What is financial literacy? Financial literacy is the ability to acquire, comprehend, and apply financial knowledge to make sound decisions in personal finance.

The survey will take approximately 5 minutes to complete. All responses are confidential and will be used for academic purposes only.

Important note: All questions must be answered for your participation to be valid.

If you have any questions or encounter any issues while completing the survey, please feel free to contact me at the following address: camille.fameree@student.uliege.be

Section 1: Demographics

Do you hold Belgian nationality?

☐ Yes

☐ No

What is your age?

☐ 18–24

☐ 25–34

☐ 35–49

☐ 50–65

What is your gender?

☐ Male

☐ Female

☐ Prefer not to say

What is your highest level of education?

☐ High school or equivalent

☐ Bachelor’s degree

☐ Master’s degree

☐ Doctorate or higher

☐ Other: ____________

What is your current occupation?

☐ Working in finance

☐ Working in a non-finance field

☐ Student in a finance-related field

☐ Student in a non-finance-related field

☐ Unemployed

☐ Retired

☐ Other: ___________

What is your annual income (before taxes)?

☐ No income

☐ Below 25,000€

☐ 25,000€–49,999€

☐ 50,000€–74,999€

☐ 75,000€–99,999€

☐ Above 100,000€

☐ Prefer not to say

<u>Section 2: Financial Literacy Assessment</u>

Instructions: For the following questions, please select the answer you believe is correct.

Suppose you had 100€ in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

☐ More than 102€

☐ Exactly 102€

☐ Less than 102€

☐ Do not know

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:

☐ More than today

☐ Exactly the same as today

☐ Less than today

☐ Do not know

Do you think that the following statement is true or false? "*Buying a single company stock usually provides a safer return than a stock mutual fund.*"

☐ True

☐ False

☐ Do not know

Do you know what compound interest is?

☐ Yes, and I understand how it works

☐ I have heard of it but am unsure how it works

☐ No, I do not know what it is

Which of the following best describes the principle of diversification?

☐ Spreading investments reduces risk

☐ Concentrating investments increases returns

☐ Diversification makes no difference to risk

☐ Do not know

Section 3: Investment Behavior

Have you ever made an investment in any of the following? (select all that apply)

☐ Savings instruments (e.g., savings accounts, CDs)

☐ Stocks

☐ Bonds

☐ Mutual funds

☐ ETFs (Exchange-Traded Funds)

☐ Real estate

☐ Derivatives (e.g., options, futures, forwards, swaps)

☐ Commodities (e.g., gold, oil)

☐ Cryptocurrencies

☐ Hedge funds

☐ Private equity

☐ Venture capital

☐ Collectibles (e.g., art, antiques)

☐ Other: ___________

☐ None

What is your primary investment strategy?

☐ Passive (replicate a market index, without trying to outperform it)

☐ Active (dynamically select securities to outperform a benchmark index)

☐ Not applicable

What is your preferred investment horizon?

☐ Short-term (less than 1 year)

☐ Medium-term (1–5 years)

☐ Long-term (more than 5 years)

☐ Not applicable

How often do you execute trades or make changes to your investment portfolio (e.g., buy/sell investments)?

☐ Daily

☐ Weekly

☐ Monthly

☐ Rarely

☐ Never

On a scale of 1 to 5, how much risk are you willing to take with your investments?

☐ 1 (Very risk-averse)

☐ 2 (Somewhat risk-averse)

☐ 3 (Neutral)

☐ 4 (Somewhat risk-tolerant)

☐ 5 (Very risk-tolerant)

French version

Merci pour votre participation à cette étude. Vos réponses m'aideront à comprendre comment la littératie financière et les caractéristiques démographiques influencent le comportement d'investissement des individus entre 18 et 65 ans.

Qu'est-ce que la littératie financière ? La littératie financière est la capacité d'acquérir, de comprendre et d'appliquer des connaissances financières afin de prendre des décisions judicieuses en matière de finances personnelles.

Le questionnaire prendra environ 5 minutes à remplir. Toutes les réponses resteront confidentielles et seront utilisées uniquement à des fins académiques.

Note importante : Il est indispensable de répondre à toutes les questions pour valider votre participation.

Si vous avez des questions ou rencontrez des problèmes lors de la complétion du questionnaire, n'hésitez pas à me contacter à l'adresse suivante : camille.fameree@student.uliege.be

Section 1 : Données Démographiques

Possédez-vous la nationalité belge ?

☐ Oui

☐ Non

Quel est votre âge ?

☐ 18–24

☐ 25–34

☐ 35–49

☐ 50–65

Quel est votre genre ?

☐ Masculin

☐ Féminin

☐ Préfère ne pas répondre

Quel est votre plus haut niveau d'éducation ?

☐ Diplôme d'études secondaires ou équivalent

☐ Bachelier

☐ Master

☐ Doctorat ou supérieur

☐ Autre : ____________

Quelle est votre profession actuelle ?

☐ Travail dans la finance

☐ Travail dans un domaine non financier

☐ Étudiant dans un domaine lié à la finance

☐ Étudiant dans un domaine non financier

☐ Sans emploi

☐ Retraité

☐ Autre : ____________

Quel est votre revenu annuel (avant impôts) ?

☐ Pas de revenu

☐ Moins de 25 000€

☐ 25 000€–49 999€

☐ 50 000€–74 999€

☐ 75 000€–99 999€

☐ Plus de 100 000€

☐ Préfère ne pas répondre

Section 2 : Évaluation de la Littératie Financière

Instructions : Pour les questions suivantes, sélectionnez la réponse que vous jugez correcte.

Supposez que vous ayez 100€ sur un compte d'épargne rapportant 2% par an. Après 5 ans, combien pensez-vous avoir sur ce compte si vous laissez l'argent fructifier ?

☐ Plus de 102€

☐ Exactement 102€

☐ Moins de 102€

☐ Je ne sais pas

Imaginez que le taux d'intérêt de votre compte d'épargne soit de 1% par an et que le taux d'inflation soit de 2% par an. Après 1 an, pourriez-vous acheter :

☐ Plus qu'aujourd'hui

☐ Exactement la même chose qu'aujourd'hui

☐ Moins qu'aujourd'hui

☐ Je ne sais pas

Pensez-vous que la déclaration suivante est vraie ou fausse ? ***« Acheter des actions d'une seule entreprise fournit généralement un rendement plus sûr qu'un fonds commun de placement. »***

☐ Vrai

☐ Faux

☐ Je ne sais pas

Savez-vous ce qu'est l'intérêt composé ?

☐ Oui, et je comprends comment cela fonctionne

☐ J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement

☐ Non, je ne sais pas ce que c'est

Lequel des énoncés suivants décrit le mieux le principe de diversification ?

☐ Répartir les investissements réduit les risques

☐ Concentrer les investissements augmente les rendements

☐ La diversification n'a aucun impact sur les risques

☐ Je ne sais pas

Section 3 : Comportement d'Investissement

Avez-vous déjà investi dans l'un des éléments suivants ? (Cochez toutes les réponses pertinentes)

☐ Instruments d'épargne (ex. : comptes d'épargne, comptes à terme)

☐ Actions

☐ Obligations

☐ Fonds communs de placement

☐ ETFs (Exchange-Traded Funds)

☐ Biens immobiliers

☐ Produits dérivés (ex. : options, futures, forwards, swaps)

☐ Matières premières (ex. : or, pétrole)

☐ Cryptomonnaies

☐ Hedge funds

☐ Private equity

☐ Venture capital

☐ Objets de collection (ex. : art, antiquités

☐ Autre : ____________

☐ Aucun

Quelle est votre stratégie d'investissement principale ?

☐ Passive (réplication d'un indice de marché, sans chercher à le surpasser)

☐ Active (sélection dynamique de titres afin de battre un indice de référence)

☐ Non applicable

Quelle est votre préférence en termes d'horizon d'investissement ?

☐ Court terme (moins d'un an)

☐ Moyen terme (1 à 5 ans)

☐ Long terme (plus de 5 ans)

☐ Non applicable

À quelle fréquence effectuez-vous des transactions ou modifiez-vous votre portefeuille d'investissements (ex. : achat/vente d'investissements) ?

☐ Quotidiennement

☐ Hebdomadairement

☐ Mensuellement

☐ Rarement

☐ Jamais

☐ Autre : ____________

Sur une échelle de 1 à 5, quel niveau de risque êtes-vous prêt(e) à prendre avec vos investissements ?

☐ 1 (Très averse au risque)

☐ 2 (Plutôt averse au risque)

☐ 3 (Neutre)

☐ 4 (Plutôt tolérant(e) au risque)

☐ 5 (Très tolérant(e) au risque)

7.2. Appendix 2 – Compiled Survey Responses Spreadsheet

This appendix presents the anonymized dataset containing all responses collected through the online questionnaire (via Google Forms). The data includes participants' answers related to demographics, financial literacy, and investment behavior. It was used as the empirical basis for the statistical analysis conducted in this research.

Horodateur	Veuillez choisir votre langue.	Possédez-vous la nationalité belge ?	Quel est votre âge ?	Quel est votre genre ?	Quel est votre plus haut niveau d'éducation ?	Quelle est votre profession actuelle ?	Quel est votre revenu annuel (avant impôts) ?	Supposez que vous ayez 100€ sur un compte d'épargne rapportant 2% par an. Après 5 ans, combien pensez-vous avoir sur ce compte si vous laissez l'argent fructifier ?	Imaginez que le taux d'intérêt de votre compte d'épargne soit de 1% par an et que le taux d'inflation soit de 2% par an. Après 1 an, pourriez-vous acheter :	Pensez-vous que la déclaration suivante est vraie ou fausse ? « *Acheter des actions d'une seule entreprise fournit généralement un rendement plus sûr qu'un fonds commun de placement.* »	Savez-vous ce qu'est l'intérêt composé ?	Lequel des énoncés suivants décrit le mieux le principe de diversification ?	Quel est votre niveau de confiance dans la gestion de vos finances personnelles ?	Avez-vous déjà investi dans l'un des éléments suivants ? (Cochez toutes les réponses pertinentes)	Quelle est votre stratégie d'investissement principale ?	Quelle est votre préférence en termes d'horizon d'investissement ?	À quelle fréquence effectuez-vous des transactions ou modifiez-vous votre portefeuille d'investissement ?	Sur une échelle de 1 à 5, quel niveau de risque êtes-vous prêt(e) à prendre avec vos investissements ?
12/26/2024 18:59:10	Français	Oui	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Mensuellement	3 (Neutre)
12/26/2024 19:07:29	Français	Oui	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	Plus de 102€	Moins qu'aujourd'hui	Faux	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, ETFs (Exchange-Traded Funds), Biens immobiliers, Matières premières (ex. : or, pétrole), Cryptomonnaies	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Mensuellement	4 (Plutôt tolérant(e) au risque)
12/26/2024 19:20:43	English	Oui	18–24	Féminin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	Plus de 102€	Moins qu'aujourd'hui	Faux	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), ETFs (Exchange-Traded Funds)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Mensuellement	4 (Plutôt tolérant(e) au risque)
12/28/2024 14:34:54	Français	Oui	35–49	Masculin	Doctorat ou supérieur	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Fonds communs de placement	Active (sélection dynamique de titres afin de battre un indice de référence)	Court terme (moins d'un an)	Quotidiennement	4 (Plutôt tolérant(e) au risque)
12/28/2024 16:36:02	Français	Oui	25–34	Féminin	Doctorat ou supérieur	Étudiant dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	2 (Plutôt averse au risque)
12/28/2024 16:41:41	Français	Oui	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Moins de 25 000€	Plus de 102€	Je ne sais pas	Je ne sais pas	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Je ne sais pas	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	2 (Plutôt averse au risque)
12/28/2024 16:42:10	Français	Oui	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Très confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), ETFs (Exchange-Traded Funds), Biens immobiliers, Cryptomonnaies	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Mensuellement	3 (Neutre)
12/28/2024 16:44:52	Français	Oui	25–34	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Répartir les investissements réduit les risques	Assez confiant(e)	Aucun	Non applicable	Moyen terme (1 à 5 ans)	Jamais	4 (Plutôt tolérant(e) au risque)
12/28/2024 16:50:46	Français	Oui	50–65	Masculin	Doctorat ou supérieur	Travail dans la finance	Préfère ne pas répondre	Plus de 102€	Moins qu'aujourd'hui	Faux	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Très confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Fonds communs de placement, Biens immobiliers, Produits dérivés (ex. : options, futures, forwards, swaps), Matières premières (ex. : or, pétrole), Hedge funds, Private equity, Objets de collection (ex. : art, antiquités)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Rarement	4 (Plutôt tolérant(e) au risque)
12/28/2024 17:33:25	Français	Oui	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Je ne sais pas	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	2 (Plutôt averse au risque)
12/28/2024 17:56:17	Français	Oui	18–24	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Fonds communs de placement, ETFs (Exchange-Traded Funds), Cryptomonnaies	Active (sélection dynamique de titres afin de battre un indice de référence)	Moyen terme (1 à 5 ans)	Hebdomadairement	4 (Plutôt tolérant(e) au risque)
12/28/2024 19:13:41	Français	Oui	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Peu confiant(e)	Aucun	Non applicable	Non applicable	Jamais	3 (Neutre)
12/28/2024 21:24:07	Français	Oui	25–34	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	Plus de 102€	Plus qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Actions, Biens immobiliers, Cryptomonnaies, Objets de collection (ex. : art, antiquités)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Court terme (moins d'un an)	Hebdomadairement	3 (Neutre)
12/29/2024 13:08:50	Français	Oui	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Retraité	25 000€–49 999€	Moins de 102€	Moins qu'aujourd'hui	Faux	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Répartir les investissements réduit les risques	Pas du tout confiant(e)	Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	3 (Neutre)
12/29/2024 13:19:26	Français	Oui	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Retraité	25 000€–49 999€	Je ne sais pas	Je ne sais pas	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Jamais	4 (Plutôt tolérant(e) au risque)

1/7/2025 20:50:52	Français	Oui	50–65	Féminin	Bachelier	Retraité	Moins de 25 000€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Pas du tout confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Jamais	1 (Très averse au risque)
1/7/2025 23:35:22	Français	Oui	35–49	Masculin	Master	Travail dans la finance	Plus de 100 000€	Plus de 102€	Moins qu'aujourd'hui	Faux	Oui, et je comprends comment cela fonctionne	Répartir les investissements réduit les risques	Très confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Fonds communs de placement, ETFs (Exchange-Traded Funds), Biens immobiliers, Matières premières (ex. : or, pétrole), Cryptomonnaies	Active (sélection dynamique de titres afin de battre un indice de référence)	Long terme (plus de 5 ans)	Mensuellement	4 (Plutôt tolérant(e) au risque)
1/8/2025 11:49:41	Français	Oui	50–65	Féminin	Master	Travail dans un domaine non financier	Plus de 100 000€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	2 (Plutôt averse au risque)
1/8/2025 11:50:38	Français	Oui	50–65	Féminin	Master	Travail dans un domaine non financier	Plus de 100 000€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Fonds communs de placement, Biens immobiliers, Matières premières (ex. : or, pétrole), Cryptomonnaies	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	4 (Plutôt tolérant(e) au risque)
1/8/2025 11:55:32	Français	Oui	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Jamais	2 (Plutôt averse au risque)
1/8/2025 11:55:38	Français	Oui	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Préfère ne pas répondre	Plus de 102€	Je ne sais pas	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Peu confiant(e)	Aucun	Non applicable	Non applicable	Jamais	3 (Neutre)
1/8/2025 12:19:40	Français	Oui	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Exactement 102€	Je ne sais pas	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Fonds communs de placement, Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Rarement	1 (Très averse au risque)
1/8/2025 12:31:11	Français	Oui	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Je ne sais pas	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Peu confiant(e)	Aucun	Non applicable	Non applicable	Jamais	1 (Très averse au risque)
1/8/2025 13:41:44	Français	Oui	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	Moins de 102€	Je ne sais pas	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	2 (Plutôt averse au risque)
1/8/2025 13:51:00	Français	Oui	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Je ne sais pas	Vrai	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme)	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	3 (Neutre)
1/8/2025 14:00:35	Français	Oui	35–49	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Répartir les investissements réduit les risques	Peu confiant(e)	Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Rarement	1 (Très averse au risque)
1/8/2025 14:05:34	Français	Oui	35–49	Féminin	Master	Travail dans un domaine non financier	75 000€–99 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	1 (Très averse au risque)
1/8/2025 14:30:23	Français	Oui	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Répartir les investissements réduit les risques	Assez confiant(e)	Aucun	Non applicable	Moyen terme (1 à 5 ans)	Jamais	2 (Plutôt averse au risque)
1/8/2025 15:46:43	Français	Oui	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions	Active (sélection dynamique de titres afin de battre un indice de référence)	Moyen terme (1 à 5 ans)	Rarement	1 (Très averse au risque)
1/8/2025 15:54:42	Français	Oui	50–65	Masculin	Bachelier	Travail dans la finance	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	J'en ai entendu parler, mais je ne suis pas sûr(e) de son fonctionnement	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions	Active (sélection dynamique de titres afin de battre un indice de référence)	Moyen terme (1 à 5 ans)	Rarement	2 (Plutôt averse au risque)
1/8/2025 19:19:20	Français	Oui	50–65	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	1 (Très averse au risque)
1/8/2025 20:11:12	Français	Oui	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	Je ne sais pas	Je ne sais pas	Faux	Non, je ne sais pas ce que c'est	Je ne sais pas	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Fonds communs de placement	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Jamais	2 (Plutôt averse au risque)
1/8/2025 20:16:48	Français	Oui	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Exactement la même chose qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Je ne sais pas	Assez confiant(e)	Biens immobiliers, Cryptomonnaies	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Jamais	2 (Plutôt averse au risque)
1/8/2025 20:29:34	Français	Oui	50–65	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	2 (Plutôt averse au risque)
1/8/2025 22:19:02	Français	Oui	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	4 (Plutôt tolérant(e) au risque)
1/9/2025 8:51:57	Français	Oui	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Exactement la même chose qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	3 (Neutre)
1/9/2025 12:00:01	Français	Oui	50–65	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	Plus de 102€	Moins qu'aujourd'hui	Faux	Non, je ne sais pas ce que c'est	Répartir les investissements réduit les risques	Assez confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Obligations, Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Long terme (plus de 5 ans)	Jamais	2 (Plutôt averse au risque)
1/9/2025 13:43:45	Français	Oui	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	Plus de 102€	Moins qu'aujourd'hui	Je ne sais pas	Non, je ne sais pas ce que c'est	Concentrer les investissements augmente les rendements	Peu confiant(e)	Instruments d'épargne (ex. : comptes d'épargne, comptes à terme), Actions, Obligations, Biens immobiliers	Passive (réplication d'un indice de marché, sans chercher à le surpasser)	Moyen terme (1 à 5 ans)	Rarement	1 (Très averse au risque)
[illegible]																		

7.3. Appendix 3 – Prepared Dataset for Analysis

This appendix includes the processed version of the survey data, formatted for statistical analysis in RStudio. Each respondent was assigned a unique identifier, and variables were recoded and structured to facilitate quantitative analysis. Demographic data were summarized, financial literacy responses were converted into binary indicators and aggregated into a composite score (0–5), and investment behavior variables were standardized using binary, ordinal, or categorical coding schemes as appropriate.

ID	Age	Gender	Education	Occupation	Income	Savings Account Growth	Impact on Purchasing Power	True or False Statement	Compound Interest	Diversification	Financial Literacy Score	Type of Investments														Primary Investment Strategy	Preferred Investment Horizon	Trading Frequency	Risk Tolerance
id_respondent	age	gender	education	occupation	income	savings_growth_above_102	inflation_impact_less	single_stock_safer_false	compound_interest_yes	diversification_reduces_risk	financial_literacy_score	investment_savings_instruments	investment_stocks	investment_bonds	investment_mutual_funds	investment_etfs	investment_real_estate	investment_derivatives	investment_commodities	investment_crypto	investment_hedge_funds	investment_private_equity	investment_venture_capital	investment_collectibles	investment_none	investment_strategy	investment_horizon	trading_frequency	risk_tolerance
1	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	3	3
2	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	1	0	1	1	0	1	1	0	0	0	0	0	0	3	3	4
3	18–24	Féminin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3	3	4
4	35–49	Masculin	Doctorat ou supérieur	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	5	4
5	25–34	Féminin	Doctorat ou supérieur	Étudiant dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2
6	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
7	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	3	3	3
8	25–34	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	0	4
9	50–65	Masculin	Doctorat ou supérieur	Travail dans la finance	NA	1	1	1	1	1	5	1	1	1	1	0	1	1	1	0	1	1	0	1	0	0	3	1	4
10	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
11	18–24	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	1	1	4	1	1	1	1	1	0	0	0	1	0	0	0	0	0	1	2	4	4
12	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
13	25–34	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	0	1	0	1	3	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	4	3
14	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Retraité	25 000€–49 999€	0	1	1	0	1	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	3
15	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Retraité	25 000€–49 999€	0	0	1	0	1	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	4
16	25–34	Féminin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	0	0	1	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	1
17	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	1	1	1	0	1	0	0	1	1	0	0	0	0	0	1	2	3	4
18	18–24	Masculin	Master	Étudiant dans un domaine non financier	Pas de revenu	1	0	0	0	1	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	1	2
19	25–34	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	0	0	1	1	0	1	1	0	0	0	0	0	0	2	3	4
20	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	1	1	5	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	3	3	4
21	25–34	Masculin	Master	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	1	1	0	0	1	0	0	0	0	0	0	2	3	4
22	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	2
23	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
24	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2
25	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
26	50–65	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2

205	18–24	Féminin	Bachelier	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
206	50–65	Féminin	Bachelier	Retraité	Moins de 25 000€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1
207	35–49	Masculin	Master	Travail dans la finance	Plus de 100 000€	1	1	1	1	1	5	1	1	1	1	1	1	0	1	1	0	0	0	0	0	1	3	3	4
208	50–65	Féminin	Master	Travail dans un domaine non financier	Plus de 100 000€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
209	50–65	Féminin	Master	Travail dans un domaine non financier	Plus de 100 000€	1	1	1	0	1	4	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	2	1	4
210	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
211	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	NA	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
212	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	0	1	0	1	2	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	3	1	1
213	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	1
214	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	0	0	1	0	1	2	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
215	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	3
216	35–49	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	1	1
217	35–49	Féminin	Master	Travail dans un domaine non financier	75 000€–99 999€	1	1	0	0	1	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
218	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	0	2
219	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	1
220	50–65	Masculin	Bachelier	Travail dans la finance	50 000€–74 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	2
221	50–65	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	0	0	1	3	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	2	1	1
222	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	2
223	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	2	0	2
224	50–65	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	2
225	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	4
226	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	1	0	1	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	3
227	50–65	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2
228	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	0	2	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	2	1	1
229	25–34	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	1	1	0	0	0	1	0	1	2	3	4
230	35–49	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	0	1	0	1	3	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	2	5	4
231	35–49	Féminin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	3	1	3
232	50–65	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	2	1	2
233	50–65	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
234	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1
235	35–49	Masculin	Master	Travail dans un domaine non financier	75 000€–99 999€	1	1	1	0	1	4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	2	0	1
236	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	0	0	1	0	1	0	0	0	0	0	1	0	0	3	3	3
237	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
238	50–65	Masculin	Bachelier	Travail dans la finance	NA	1	1	1	1	1	5	1	1	1	1	1	1	1	1	0	1	0	0	0	0	1	3	3	4
239	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	NA	1	1	1	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
240	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	3
241	50–65	Masculin	Master	Travail dans un domaine non financier	Plus de 100 000€	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
242	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
243	50–65	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	3	1	2
244	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
245	18–24	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	1	0	0	0	0	0	0	1	2	0	3
246	35–49	Masculin	Master	Travail dans la finance	Plus de 100 000€	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	0	1	0	0	0	1	3	3	4
247	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	4
248	25–34	Féminin	Doctorat ou supérieur	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	1	2
249	18–24	Féminin	Master	Étudiant dans un domaine non financier	Pas de revenu	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
250	35–49	Masculin	Master	Travail dans la finance	Plus de 100 000€	1	1	1	1	1	5	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	3	1	3
251	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	1	1	1	0	0	0	1	0	0	0	0	0	0	3	3	3
252	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	0	0	1	1	0	0	0	0	0	0	0	0	0	3	3	3
253	35–49	Masculin	Bachelier	Travail dans la finance	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2
254	35–49	Féminin	Master	Travail dans un domaine non financier	Plus de 100 000€	1	1	0	0	0	2	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
255	35–49	Masculin	Master	Travail dans la finance	Plus de 100 000€	1	1	1	1	1	5	1	1	1	1	1	1	0	1	0	0	0	0	1	0	1	3	3	4
256	35–49	Féminin	Master	Travail dans un domaine non financier	75 000€–99 999€	1	1	1	1	1	5	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
257	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	3	3	4
258	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	3	4	4
259	25–34	Masculin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	3	3	2
260	18–24	Masculin	Bachelier	Travail dans un domaine non financier	NA	1	0	1	1	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	3	3
261	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2
262	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	0	1	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
263	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
264	50–65	Masculin	Bachelier	Travail dans un domaine non financier	75 000€–99 999€	1	1	1	1	1	5	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	3	1	3
265	18–24	Masculin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	0	3
266	18–24	Féminin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3
267	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	0	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	3	3	3
268	18–24	Masculin	Bachelier	Travail dans la finance	50 000€–74 999€	1	1	1	0	1	4	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	1	1	4
269	18–24	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1	3	1	3
270	25–34	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	1	2
271	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	2	4	5
272	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	2	1	1
273	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	1	2
274	18–24	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3
275	18–24	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	0	0	1	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	4
276	35–49	Féminin	Bachelier	Travail dans la finance	25 000€–49 999€	1	1	0	0	1	3	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	2	1	2
277	25–34	Féminin	Bachelier	Étudiant dans un domaine non financier	Moins de 25 000€	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	3
278	18–24	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	1
279	50–65	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	0	0	1	0	0	0	0	0	0	0	0	1	3	1	2
280	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	1	1	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
281	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	1	1	1	1	4	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	3
282	18–24	Féminin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
283	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3
284	18–24	Féminin	Bachelier	Travail dans un domaine non financier	Moins de 25 000€	1	1	0	1	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
285	18–24	Masculin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	3	3	3
286	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	50 000€–74 999€	1	0	1	1	0	3	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	3	1	2
287	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	2	1	2
288	18–24	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	2	3	1
289	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	1	1	1	0	1	0	0	0	1	0	0	0	0	0	1	3	1	4
290	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	1	1	0	0	2	1	0	0	1	0	1	0	0	0	0	0	0	0	0	1	3	0	4
291	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	1	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	4	1
292	35–49	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Plus de 100 000€	0	1	1	0	0	2	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	3	1	3
293	18–24	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	2
294	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Moins de 25 000€	1	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	2
295	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	2
296	25–34	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	3	3	2
297	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	2
298	18–24	Féminin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	1	0	1	1	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
299	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	1	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	3	5
300	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	50 000€–74 999€	1	0	0	1	1	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	4	2
301	18–24	Féminin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	0	1	1	1	1	4	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	3
302	18–24	Féminin	Bachelier	Travail dans un domaine non financier	Moins de 25 000€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	4
303	18–24	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	1	0	1	3	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	2	0	3
304	25–34	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	0	4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	3	1	3
305	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
306	18–24	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
307	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	2	1	5
308	18–24	Féminin	Bachelier	Sans emploi	Pas de revenu	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
309	25–34	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	3	0	3
310	50–65	Féminin	Bachelier	Travail dans un domaine non financier	75 000€–99 999€	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	1
311	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	1	1	5	1	1	1	1	1	1	0	0	0	1	1	0	0	0	0	3	3	5
312	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	1	1	5	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	3	3	2
313	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1
314	18–24	Masculin	Master	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	1	1	0	1	0	0	1	1	0	0	0	0	0	1	2	3	4
315	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	4
316	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	1	0	0	0	1	0	1	0	0	0	0	3	3	3
317	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	3	1	2
318	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	1	2
319	18–24	Masculin	Master	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	1	0	0	0	0	0	0	0	0	0	1	3	3	5
320	18–24	Masculin	Master	Travail dans la finance	50 000€–74 999€	1	1	1	1	1	5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	3	4
321	18–24	Masculin	Master	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	3	3	2
322	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	1	3
323	25–34	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	1	1	5	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	0	2
324	18–24	Féminin	Bachelier	Travail dans un domaine non financier	NA	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3
325	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	3	4	4
326	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	3	4	4
327	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	1	3	2
328	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
329	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	0	1	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	1	1	3
330	25–34	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
331	18–24	Féminin	Bachelier	Travail dans un domaine non financier	Moins de 25 000€	1	0	1	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	1	2
332	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	0	1	1	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
333	18–24	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	5	3
334	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	Moins de 25 000€	1	1	1	1	1	5	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	1	2
335	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Pas de revenu	0	1	1	0	1	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	2
336	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3	5	3
337	18–24	Féminin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
338	50–65	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	0	0	1	0	0	0	0	0	0	0	0	1	3	1	1
339	18–24	Féminin	Master	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	1	1	5	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	3	1	4
340	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
341	18–24	Féminin	Bachelier	Étudiant dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
342	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Étudiant dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	3
343	25–34	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	2
344	25–34	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1
345	18–24	Féminin	Master	Étudiant dans un domaine non financier	Pas de revenu	0	1	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	3
346	25–34	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	1	2	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	3
347	18–24	Masculin	Bachelier	Travail dans la finance	Moins de 25 000€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
348	18–24	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	2
349	50–65	Masculin	Master	Travail dans la finance	Plus de 100 000€	1	1	1	1	1	5	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	3	1	1
350	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
351	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	Moins de 25 000€	1	0	1	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	4
352	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	1	3
353	25–34	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	1	4
354	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Sans emploi	Pas de revenu	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	3
355	25–34	Masculin	Bachelier	Étudiant dans un domaine non financier	Moins de 25 000€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	3
356	18–24	Féminin	Master	Étudiant dans un domaine non financier	Moins de 25 000€	1	1	1	0	1	4	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	3	1	2
357	25–34	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
358	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	5
359	50–65	Masculin	Doctorat ou supérieur	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	3	1	4
360	35–49	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
361	18–24	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	4
362	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
363	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	NA	1	1	1	1	1	5	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	2	1	4
364	50–65	Féminin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
365	50–65	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	0	1	1	0	0	0	0	0	1	0	1	3	1	3
366	35–49	Féminin	Doctorat ou supérieur	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	2	1	2
367	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	0	1	1	0	1	3	1	1	1	1	0	1	0	0	0	0	0	0	1	0	1	2	3	4
368	25–34	Masculin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	1	4	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	3	3	3
369	25–34	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	0	0	3	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	1	5
370	25–34	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	1	1	5	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	2	1	2
371	18–24	Féminin	Master	Travail dans un domaine non financier	25 000€–49 999€	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	5
372	50–65	Masculin	Master	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	5	2
373	18–24	Féminin	Master	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	0	1	4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3	3	2
374	18–24	Masculin	Master	Sans emploi	Pas de revenu	1	1	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	1
375	18–24	Masculin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	2	1	3
376	50–65	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	5
377	18–24	Féminin	Bachelier	Travail dans un domaine non financier	NA	1	1	0	0	0	2	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	3	0	3
378	18–24	Masculin	Bachelier	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	1	5
379	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	1	0	0	1	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3
380	35–49	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	1	1	1	0	1	1	1	0	0	1	0	0	0	1	2	1	3
381	50–65	Masculin	Master	Travail dans un domaine non financier	Plus de 100 000€	0	1	1	0	1	3	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	3	1	2
382	35–49	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	0	0	1	0	1	2	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	3	1	2
383	18–24	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	2	1	4
384	35–49	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	0	1	1	1	1	4	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	2	4	4
385	35–49	Masculin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	1	1	5	1	1	0	0	1	0	0	0	1	0	1	0	0	0	1	3	3	4
386	25–34	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	1	1	5	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3	1	3
387	35–49	Féminin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	1	1	1	0	0	1	0	0	1	0	0	0	0	0	0	1	1	1
388	18–24	Masculin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	0	1	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3	2
389	18–24	Féminin	Master	Étudiant dans un domaine non financier	Moins de 25 000€	1	1	0	1	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	NA	0	1
390	35–49	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	Moins de 25 000€	1	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1
391	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	2	1	4
392	18–24	Masculin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
393	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3
394	25–34	Masculin	Bachelier	Travail dans un domaine non financier	Moins de 25 000€	1	1	1	1	1	5	0	1	1	0	1	0	0	0	1	0	0	0	0	0	0	2	4	3
395	50–65	Féminin	Bachelier	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	0	1	4	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	3	3	4
396	18–24	Féminin	Bachelier	Étudiant dans un domaine non financier	Pas de revenu	1	1	1	1	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	0	1
397	25–34	Féminin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
398	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	1	1	1	1	5	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3	2	4
399	50–65	Masculin	Diplôme d'études secondaires ou équivalent	Retraité	NA	1	1	0	0	0	2	0	1	0	0	0	1	0	0	0	0	0	0	1	0	1	2	1	1
400	18–24	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	NA	1	0	1	0	1	3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	3
401	35–49	Féminin	Master	Travail dans un domaine non financier	NA	1	1	1	0	1	4	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	2	3	4
402	50–65	Masculin	Master	Travail dans la finance	NA	1	1	1	1	1	5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	3	1	3
403	25–34	Masculin	Master	Travail dans un domaine non financier	50 000€–74 999€	1	1	1	1	1	5	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	3	3	5
404	50–65	Masculin	Master	Travail dans la finance	75 000€–99 999€	1	1	1	1	1	5	1	1	0	1	0	1	1	0	0	0	0	0	0	0	0	3	1	3
405	25–34	Féminin	Master	Travail dans la finance	25 000€–49 999€	1	1	1	1	1	5	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	3	0	3
406	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
407	25–34	Féminin	Diplôme d'études secondaires ou équivalent	Travail dans un domaine non financier	25 000€–49 999€	1	0	0	0	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1
408	18–24	Féminin	Master	Étudiant dans un domaine non financier	Pas de revenu	1	0	1	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	0	3
409	25–34	Masculin	Bachelier	Étudiant dans un domaine lié à la finance	Moins de 25 000€	1	0	0	1	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	NA	2	4	1
410	18–24	Féminin	Master	Étudiant dans un domaine lié à la finance	Pas de revenu	1	1	1	1	1	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	2
411	25–34	Masculin	Bachelier	Travail dans un domaine non financier	25 000€–49 999€	1	1	1	1	1	5	1	1	1	0	1	1	1	1	1	0	0	0	0	0	1	3	3	5

7.4. Appendix 4 – RStudio Scripts

This appendix contains the R scripts used to perform the statistical analyses presented in the thesis. These scripts were developed and executed in RStudio and correspond to the various steps of the analysis: (1) generation of the correlation matrix, (2) examination of the impact of demographic characteristics on financial literacy (Stage 1), and (3) assessment of how financial literacy influences investment behavior (Stage 2), including analyses of asset allocation, primary investment strategy (active versus passive), investment horizon preferences, risk tolerance, and trading frequency. These scripts were applied to the prepared dataset provided in *Appendix 3*.

Correlation Matrix

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)
library(dplyr)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Convert "NA" string to actual NA (missing value)
data$income[data$income == "NA"] <- NA

# Remove rows where 'income' is NA
data <- data %>%
  filter(!is.na(income))

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Income (low → high)
    income = ordered(income, levels = c("Pas de revenu", "Moins de 25 000€", "25 000€-49 999€", "50 000€-74 999€", "75 000€-99 999€", "Plus de 100 000€"),
                     labels = c("No income", "<€25K", "€25K-€49K", "€50K-€74K", "€75K-€99K", ">€100K"), exclude = NULL),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

# Convert financial_literacy_score to ordered factor
data$financial_literacy_score <- ordered(data$financial_literacy_score, levels = 0:5)

# Step 4: Create correlation matrix
# Cramer's V for categorical-categorical
cramer_v <- function(x, y) {
  tbl <- table(x, y)
  chi2 <- suppressWarnings(chisq.test(tbl, correct = FALSE))
  n <- sum(tbl)
  phi2 <- chi2$statistic / n
  r <- nrow(tbl)
  k <- ncol(tbl)
  return(as.numeric(sqrt(phi2 / min(r - 1, k - 1))))
}

# Spearman's rho for numeric-numeric or ordinal-ordinal
spearman_corr <- function(x, y) {
  return(as.numeric(cor(as.numeric(x), as.numeric(y), method = "spearman", use = "complete.obs")))
}

# Determine type of association to compute
smart_assoc <- function(x, y) {
  if (is.factor(x) && is.factor(y)) {
    cramer_v(x, y)
  } else {
    spearman_corr(x, y)
  }
}

# Select variables
vars <- data %>% select(age, gender, education, occupation, income, financial_literacy_score, investment_savings_instruments, investment_stocks, investment_bonds, investment_mutual_funds,
                        investment_etfs, investment_real_estate, investment_derivatives, investment_commodities, investment_crypto, investment_collectibles,investment_none,
                        investment_strategy, investment_horizon, trading_frequency, risk_tolerance)

# Initialize correlation matrix
cor_matrix <- matrix(NA, ncol(vars), ncol(vars))
colnames(cor_matrix) <- rownames(cor_matrix) <- names(vars)

# Fill matrix
for (i in 1:ncol(vars)) {
  for (j in 1:ncol(vars)) {
    if (i == j) {
      cor_matrix[i, j] <- 1
    } else {
      cor_matrix[i, j] <- smart_assoc(vars[[i]], vars[[j]])
    }
  }
}

# View correlation matrix
print(round(cor_matrix, 3))
```

Stage 1: Impact of Demographic Characteristics on Financial Literacy

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

# Convert financial_literacy_score to ordered factor
data$financial_literacy_score <- ordered(data$financial_literacy_score, levels = 0:5)

# Step 4: Fit ordinal logistic regression model
model <- polr(financial_literacy_score ~ age + gender + education + occupation, data = data, Hess = TRUE, method = "logistic")

# Step 5: Display model summary (coefficients and statistics)
summary(model)

# Step 6: Calculate p-values for model coefficients
coefficients <- coef(summary(model))
p_values <- pnorm(abs(coefficients[, "t value"]), lower.tail = FALSE) * 2
# Step 7: Compute confidence intervals for model coefficients
conf_int <- confint(model)
conf_df <- as.data.frame(conf_int)
conf_df_main <- conf_df[1:nrow(coefficients), ]
colnames(conf_df_main) <- c("CI Lower", "CI Upper")

# Step 8: Calculate odds ratios and their confidence intervals
odds_ratios <- exp(coef(model))
odds_ratios_main <- odds_ratios[1:nrow(coefficients)]
odds_ratio_ci <- exp(conf_df)
odds_ratio_ci_main <- odds_ratio_ci[1:nrow(coefficients), ]
colnames(odds_ratio_ci_main) <- c("OR CI Lower", "OR CI Upper")

# Step 9: Create results summary table
results_table <- cbind(Estimate = coefficients[, "Value"], Std.Error = coefficients[, "Std. Error"], `t value` = coefficients[, "t value"], `p value` = p_values,
                       `CI Lower` = conf_df_main$`CI Lower`, `CI Upper` = conf_df_main$`CI Upper`, `Odds Ratio` = odds_ratios_main,
                       `OR CI Lower` = odds_ratio_ci_main$`OR CI Lower`, `OR CI Upper` = odds_ratio_ci_main$`OR CI Upper`)

# Step 10: Format results table (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 11: Display formatted results table
print(results_table)

# Step 12: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 13: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

<u>Stage 2: Impact of Financial Literacy on Investment Behavior</u>

<u>Asset Allocation</u>

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

# Step 3: Define investment variables and control variables for modeling
investment_columns <- c("investment_savings_instruments", "investment_stocks", "investment_bonds", "investment_mutual_funds", "investment_etfs", "investment_real_estate",
                        "investment_derivatives", "investment_commodities", "investment_crypto", "investment_collectibles")

control_vars <- c("financial_literacy_score", "age", "gender", "education ", "occupation ")

# Step 4: Run logistic regression models for each investment type
results <- lapply(investment_columns, function(investment) {

  # Step 4.1: Define model formula
  formula <- as.formula(paste(investment, "~", paste(control_vars, collapse = " + ")))

  # Step 4.2: Fit logistic regression model
  model <- glm(formula, data = data, family = binomial(link = "logit"))
  # Step 4.3: Compute confidence intervals for model coefficients
  conf_int <- confint(model)

  # Step 4.4: Compute odds ratios and confidence intervals
  odds_ratios <- exp(coef(model))
  odds_ratio_ci <- exp(confint(model))

  # Step 4.5: Calculate pseudo R-squared and multicollinearity (VIF)
  pseudo_r2 <- pscl::pR2(model)
  VIF <- car::vif(model)

  # Step 4.6: Create model results table
  results_table <- cbind(Estimate = coef(model), Std.Error = summary(model)$coefficients[, 2], `z value` = summary(model)$coefficients[, 3], `p value` = summary(model)$coefficients[, 4],
                         CI_lower = conf_int[, 1], CI_upper = conf_int[, 2], OddsRatio = odds_ratios, OR_CI_lower = odds_ratio_ci[, 1], OR_CI_upper = odds_ratio_ci[, 2])

  # Step 4.7: Format results table
  results_table <- as.data.frame(results_table) %>%
    mutate(across(where(is.numeric), ~ round(., 4)))

  # Step 4.8: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
  Mc_Fadden_R2 <- pR2(model)
  results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
    mutate(across(where(is.numeric), ~ round(., 4)))

  # Step 4.9: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
  VIF <- car::vif(model)
  results_VIF <- as.data.frame(VIF) %>%
    mutate(across(where(is.numeric), ~ round(., 4)))

  # Step 4.10: Return model output as a structured list (for each investment)
  return(list(model = model, summary = summary(model), results_table = results_table, results_R2 = results_R2, results_VIF = results_VIF))
})

# Step 5: Name each result list by its corresponding investment type
names(results) <- investment_columns

# Step 6: Display results for each investment model
for (investment in investment_columns) {
  cat("\nResults for:", investment, "\n")
  print(results[[investment]]$results_table)
  cat("\n----------------------------\n")
}
```

<u>No Investment</u>

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

# Step 4: Fit binary logistic regression model
model_none <- glm(investment_none ~ financial_literacy_score + age + gender + education + occupation, data = data, family = binomial(link = "logit"))

# Step 5: Display model summary (coefficients and statistics)
summary(model_none)

# Step 6: Compute confidence intervals for model coefficients
conf_int <- confint(model_none)

# Step 7: Calculate odds ratios and their confidence intervals
odds_ratios <- exp(coef(model_none))
odds_ratio_ci <- exp(confint(model_none))
# Step 8: Create results summary table
results_table <- cbind(Estimate = coef(model_none), Std.Error = summary(model_none)$coefficients[, 2], `z value` = summary(model_none)$coefficients[, 3],
                       `p value` = summary(model_none)$coefficients[, 4], CI_lower = conf_int[, 1], CI_upper = conf_int[, 2], OddsRatio = odds_ratios,
                       OR_CI_lower = odds_ratio_ci[, 1], OR_CI_upper = odds_ratio_ci[, 2])

# Step 9: Format results table for display (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 10: Display the formatted results table
print(results_table)

# Step 11: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model_none)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 12: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model_none)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

Active versus Passive Investment Strategy

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Convert "NA" string to actual NA (missing value)
data$investment_strategy[data$investment_strategy == "NA"] <- NA

# Remove rows where investment_strategy is NA
data <- data %>%
  filter(!is.na(investment_strategy))

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))

  )

# Convert investment_strategy into numeric
data$investment_strategy <- as.numeric(data$investment_strategy)

# Step 4: Fit binary logistic regression model
model <- glm(investment_strategy ~ financial_literacy_score + age + gender + education + occupation, data = data, family = binomial(link = "logit"))
# Step 5: Display model summary
summary(model)

# Step 6: Compute confidence intervals for model coefficients
conf_int <- confint(model)

# Step 7: Calculate odds ratios and their confidence intervals
odds_ratios <- exp(coef(model))
odds_ratio_ci <- exp(confint(model))

# Step 8: Create results summary table
results_table <- cbind(Estimate = coef(model), Std.Error = summary(model)$coefficients[, 2], `z value` = summary(model)$coefficients[, 3], `p value` = summary(model)$coefficients[, 4],
                       CI_lower = conf_int[, 1], CI_upper = conf_int[, 2], OddsRatio = odds_ratios, OR_CI_lower = odds_ratio_ci[, 1], OR_CI_upper = odds_ratio_ci[, 2])

# Step 9: Format results table for display (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 10: Display the formatted results table
print(results_table)

# Step 11: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 12: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

Investment Horizon Preferences

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Convert "NA" string to actual NA (missing value)
data$investment_horizon[data$investment_horizon == "NA"] <- NA

# Remove rows where investment_horizon is NA
data <- data %>%
  filter(!is.na(investment_horizon))

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))

  )

# Convert investment_horizon into numeric
data$ investment_horizon <- as.numeric(data$ investment_horizon)

# Convert investment_horizon to ordered factor
data $investment_horizon <- ordered(data$investment_horizon, levels = c(1, 2, 3), labels = c("short term", "medium term", "long term"))
# Step 4: Fit probit regression model
model <- polr(investment_horizon ~ financial_literacy_score + age + gender + education + occupation, data = data, Hess = TRUE, method = "probit")

# Step 5: Display model summary
summary(model)

# Step 6: Calculate p-values for model coefficients
coefficients <- coef(summary(model))
p_values <- pnorm(abs(coefficients[, "t value"]), lower.tail = FALSE) * 2

# Step 7: Compute confidence intervals for model coefficients
conf_int <- confint(model)
conf_df <- as.data.frame(conf_int)
conf_df_main <- conf_df[1:nrow(coefficients), ]
colnames(conf_df_main) <- c("CI Lower", "CI Upper")

# Step 8: Create results summary table
results_table <- cbind(Estimate = coefficients[, "Value"], Std.Error = coefficients[, "Std. Error"], `t value` = coefficients[, "t value"], `p value` = p_values,
                       `CI Lower` = conf_df_main$`CI Lower`, `CI Upper` = conf_df_main$`CI Upper`)

# Step 9: Format results table for display (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 10: Display the formatted results table
print(results_table)

# Step 11: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 12: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

<u>Risk Tolerance</u>

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

# Convert risk_tolerance to ordered factor
data$risk_tolerance <- ordered (data$risk_tolerance, levels = c(1, 2, 3, 4, 5), labels = c("Very risk-averse",  "Somewhat risk-averse", "Neutral", "Somewhat risk-tolerant", "Very risk-tolerant"))

# Step 4: Fit ordinal logistic regression model
model <- polr(risk_tolerance ~ financial_literacy_score + age + gender + education + occupation, data = data, Hess = TRUE, method = "logistic")

# Step 5: Display model summary
summary(model)

# Step 6: Calculate p-values for model coefficients
coefficients <- coef(summary(model))
p_values <- pnorm(abs(coefficients[, "t value"]), lower.tail = FALSE) * 2
# Step 7: Compute confidence intervals for model coefficients
conf_int <- confint(model)
conf_df <- as.data.frame(conf_int)
conf_df_main <- conf_df[1:nrow(coefficients), ]
colnames(conf_df_main) <- c("CI Lower", "CI Upper")

# Step 8: Calculate odds ratios and their confidence intervals
odds_ratios <- exp(coef(model))
odds_ratios_main <- odds_ratios[1:nrow(coefficients)]
odds_ratio_ci <- exp(conf_df)
odds_ratio_ci_main <- odds_ratio_ci[1:nrow(coefficients), ]
colnames(odds_ratio_ci_main) <- c("OR CI Lower", "OR CI Upper")

# Step 9: Create results summary table
results_table <- cbind(Estimate = coefficients[, "Value"], Std.Error = coefficients[, "Std. Error"], `t value` = coefficients[, "t value"], `p value` = p_values,
                       `CI Lower` = conf_df_main$`CI Lower`, `CI Upper` = conf_df_main$`CI Upper`, `Odds Ratio` = odds_ratios_main,
                       `OR CI Lower` = odds_ratio_ci_main$`OR CI Lower`, `OR CI Upper` = odds_ratio_ci_main$`OR CI Upper`)

# Step 10: Format results table for display (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 11: Display the formatted results table
print(results_table)

# Step 12: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 13: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

Trading Frequency

```r
# Step 1: Load required libraries
library(readxl)
library(MASS)
library(tidyverse)
library(pscl)
library(broom)
library(performance)
library(effects)
library(car)

# Step 2: Import data from Excel file
data <- read_excel("financial_literacy.xlsx", sheet = "data 2", skip = 1)

# Step 3: Convert variables to (un)ordered factors, removing NAs rows for income

# Proceed with the mutations and factor conversions
data <- data %>%
  mutate(
    # Age (young → old)
    age = ordered(age, levels = c("18-24", "25-34", "35-49", "50-65"), labels = c("18-24", "25-34", "35-49", "50-65")),

    # Education (low → high)
    education = ordered(education, levels = c("Diplôme d'études secondaires ou équivalent", "Bachelier", "Master", "Doctorat ou supérieur"),
                        labels = c("High school or equivalent", "Bachelor", "Master", "PhD or higher")),

    # Gender
    gender = factor(gender, levels = c("Féminin", "Masculin"), labels = c("Female", "Male")),

    # Occupation
    occupation = factor(occupation, levels = c("Sans emploi", "Travail dans la finance", "Travail dans un domaine non financier", "Étudiant dans un domaine lié à la finance",
                                               "Étudiant dans un domaine non financier", "Retraité"),
                        labels = c("Unemployed", "Finance job", "Non-finance job", "Finance student", "Non-finance student", "Retired"))
  )

#Convert trading_frequency to ordered factor
data$trading_frequency <- ordered(data$trading_frequency, levels = c(0, 1, 2, 3, 4, 5), labels = c("never", "rarely", "annually", "monthly", "weekly", "daily"))

# Step 4: Fit probit regression model
model <- polr(trading_frequency ~ financial_literacy_score + age + gender + education + occupation, data = data, Hess = TRUE, method = "probit")

# Step 5: Display model summary
summary(model)

# Step 6: Calculate p-values for model coefficients
coefficients <- coef(summary(model))
p_values <- pnorm(abs(coefficients[, "t value"]), lower.tail = FALSE) * 2
# Step 7: Compute confidence intervals for model coefficients
conf_int <- confint(model)
conf_df <- as.data.frame(conf_int)
conf_df_main <- conf_df[1:nrow(coefficients), ]
colnames(conf_df_main) <- c("CI Lower", "CI Upper")

# Step 8: Create results summary table
results_table <- cbind(Estimate = coefficients[, "Value"], Std.Error = coefficients[, "Std. Error"], `t value` = coefficients[, "t value"], `p value` = p_values,
                       `CI Lower` = conf_df_main$`CI Lower`, `CI Upper` = conf_df_main$`CI Upper`)

# Step 9: Format results table for display (round numeric values)
results_table <- as.data.frame(results_table) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 10: Display the formatted results table
print(results_table)

# Step 11: Evaluate model fit using McFadden's pseudo R-squared and format results_R2 table (round numeric values)
Mc_Fadden_R2 <- pR2(model)
results_R2 <- as.data.frame(Mc_Fadden_R2) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))

# Step 12: Check multicollinearity using Variance Inflation Factor (VIF) and format results_VIF table (round numeric values)
VIF <- car::vif(model)
results_VIF <- as.data.frame(VIF) %>%
  mutate(across(where(is.numeric), ~ round(., 4)))
```

7.5. Appendix 5 – Complete Correlation Matrix

This appendix presents the full correlation matrix used to evaluate potential multicollinearity issues prior to conducting regression analyses, ensuring the reliability of the statistical models employed in the study.

	Age	Gender	Education	Occupation	Income	Financial Literacy Score	Savings Instruments	Stocks	Bonds	Mutual Funds
Age	1	0.14844858	0.1502784	0.408938168	0.396010597	0.20160246	0.09618155	0.044160851	0.14490357	0.248750949
Gender	0.148448577	1	0.06351511	0.280936696	0.137566834	0.42549779	0.05861468	0.306892216	0.17230421	0.190572842
Education	0.150278397	0.06351511	1	0.194859998	0.193213837	0.2508962	0.05004747	0.138285364	0.19489028	0.06661398
Occupation	0.408938168	0.2809367	0.19486	1	0.408602509	0.26340625	-0.24130608	-0.07226702	-0.16155001	-0.226510941
Income	0.396010597	0.13756683	0.19321384	0.408602509	1	0.17982152	0.19087636	0.068741889	0.16786684	0.269673514
Financial Literacy Score	0.201602461	0.42549779	0.2508962	0.263406247	0.17982152	1	0.15400107	0.380946404	0.24351024	0.186563583
Savings Instruments	0.096181547	0.05861468	0.05004747	-0.241306083	0.19087636	0.15400107	1	0.211397495	0.23308004	0.170281451
Stocks	0.044160851	0.30689222	0.13828536	-0.07226702	0.068741889	0.3809464	0.2113975	1	0.45674832	0.275660409
Bonds	0.144903568	0.17230421	0.19489028	-0.161550011	0.167866841	0.24351024	0.23308004	0.456748322	1	0.405880209
Mutual Funds	0.248750949	0.19057284	0.06661398	-0.226510941	0.269673514	0.18656358	0.17028145	0.275660409	0.40588021	1
ETFs	-0.260515594	0.4172676	0.17281591	0.054848639	-0.140235118	0.46014294	0.14097112	0.426665195	0.26610802	0.054557621
Real Estate	0.377942539	-0.04421175	0.02209175	-0.238650979	0.357679536	-0.07085231	0.13432764	0.053174652	0.18161513	0.149813705
Derivatives	0.001233546	0.25530266	0.1273961	-0.117596911	0.057587633	0.25230929	0.03829806	0.271532718	0.16208549	0.209091119
Commodities	0.029315421	0.12803102	0.14663838	-0.106679188	0.123394346	0.13199152	0.08614634	0.19030335	0.14629357	0.088552477
Cryptocurrencies	-0.139170491	0.33464055	0.10546089	0.003558482	-0.041216313	0.33931422	0.01927212	0.261316058	0.13459262	-0.020061824
Collectibles	-0.026842803	0.07908721	0.09418442	-0.084880028	0.015234039	0.10877003	0.02400908	0.070127746	0.01703646	-0.004984243
No Investment	-0.18249648	-0.15223591	-0.05653322	0.220055951	-0.241811573	-0.15073337	-0.69299662	-0.286409059	-0.20230428	-0.173984641
Investment Strategy	0.007021338	0.10884377	0.08791761	-0.06405884	0.079843396	0.15871269	-0.02265744	0.406776475	0.18246756	0.139156918
Investment Horizon	0.009950999	0.07369175	0.09262379	-0.065778407	0.032200588	0.13335563	0.23115506	-0.008283127	0.04439435	0.062767044
Trading Frequency	-0.037021284	0.38295089	0.03284325	-0.052971409	0.005423751	0.32477594	0.2357311	0.459433265	0.29666779	0.198584684
Risk Tolerance	-0.243367403	0.36144024	0.11089602	0.043578564	-0.106679818	0.32624387	-0.0226338	0.312674915	0.17955141	0.158267872

	ETFs	Real Estate	Derivatives	Commodities	Cryptocurrencies	Collectibles	No Investment	Investment Strategy	Investment Horizon	Trading Frequency	Risk Tolerance
Age	-0.26051559	0.37794254	0.001233546	0.029315421	-0.139170491	-0.026842803	-0.18249648	0.007021338	0.009950999	-0.037021284	-0.2433674
Gender	0.4172676	-0.04421175	0.255302664	0.128031018	0.334640549	0.079087209	-0.15223591	0.108843774	0.073691747	0.382950887	0.36144024
Education	0.17281591	0.02209175	0.127396103	0.146638378	0.105460891	0.094184419	-0.05653322	0.087917612	0.092623786	0.032843254	0.11089602
Occupation	0.05484864	-0.23865098	-0.117596911	-0.106679188	0.003558482	-0.084880028	0.22005595	-0.06405884	-0.065778407	-0.052971409	0.04357856
Income	-0.14023512	0.35767954	0.057587633	0.123394346	-0.041216313	0.015234039	-0.24181157	0.079843396	0.032200588	0.005423751	-0.10667982
Financial Literacy Score	0.46014294	-0.07085231	0.252309294	0.13199152	0.33931422	0.108770028	-0.15073337	0.15871269	0.133355628	0.324775941	0.32624387
Savings Instruments	0.14097112	0.13432764	0.038298059	0.086146338	0.019272122	0.024009083	-0.69299662	-0.022657442	0.231155064	0.235731099	-0.0226338
Stocks	0.42666519	0.05317465	0.271532718	0.190303351	0.261316058	0.070127746	-0.28640906	0.406776475	-0.008283127	0.459433265	0.31267491
Bonds	0.26610802	0.18161513	0.162085485	0.146293568	0.134592619	0.017036458	-0.20230428	0.182467561	0.04439435	0.296667786	0.17955141
Mutual Funds	0.05455762	0.1498137	0.209091119	0.088552477	-0.020061824	-0.004984243	-0.17398464	0.139156918	0.062767044	0.198584684	0.15826787
ETFs	1	-0.08736148	0.293220135	0.245106774	0.523383858	0.077038141	-0.17558906	0.061617101	0.205422209	0.4434223	0.36306751
Real Estate	-0.08736148	1	0.070208224	0.146397916	-0.066414079	0.078547056	-0.23465023	0.07092377	0.040306878	0.072970814	-0.04991812
Derivatives	0.29322014	0.07020822	1	0.183210191	0.131198918	0.156529216	-0.09737559	0.093541247	0.091564854	0.236609437	0.1792808
Commodities	0.24510677	0.14639792	0.183210191	1	0.213781038	0.129812358	-0.10818129	0.189678688	0.000749729	0.169183531	0.20411097
Cryptocurrencies	0.52338386	-0.06641408	0.131198918	0.213781038	1	0.064365063	-0.20539951	0.157475944	-0.010388425	0.369971589	0.3056114
Collectibles	0.07703814	0.07854706	0.156529216	0.129812358	0.064365063	1	-0.1017996	0.133917827	-0.019745045	0.164519976	0.19033438
No Investment	-0.17558906	-0.23465023	-0.097375592	-0.108181289	-0.205399513	-0.101799595	1	-0.067946193	-0.175241505	-0.347268894	-0.04860297
Investment Strategy	0.0616171	0.07092377	0.093541247	0.189678688	0.157475944	0.133917827	-0.06794619	1	-0.010314559	0.232178323	0.28253887
Investment Horizon	0.20542221	0.04030688	0.091564854	0.000749729	-0.010388425	-0.019745045	-0.1752415	-0.010314558	1	-0.023899888	0.03990609
Trading Frequency	0.4434223	0.07297081	0.236609437	0.169183531	0.369971589	0.164519976	-0.34726889	0.232178323	-0.023899888	1	0.38058769
Risk Tolerance	0.36306751	-0.04991812	0.179280804	0.204110972	0.305611402	0.190334378	-0.04860297	0.282538872	0.039906088	0.380587694	1

7.6. Appendix 6 – Detailed Regression Outputs

This appendix provides the complete results of the regression analyses conducted in the study. It includes outputs from Stage 1, which examines the impact of demographic characteristics on financial literacy, and Stage 2, which investigates the influence of financial literacy on various dimensions of investment behavior. For each model, regression outputs, model fit values, and multicollinearity diagnostics are reported.

Stage 1: Impact of Demographic Characteristics on Financial Literacy

	Estimate	Std.Error	t value	p value	CI Lower	CI Upper	Odds Ratio	OR CI Lower	OR CI Upper
Age.L	-0.1405	0.2213	-0.6348	0.5256	-0.5751	0.2931	0.8690	0.5627	1.3406
Age.Q	0.3245	0.2174	1.4928	0.1355	-0.1016	0.7513	1.3834	0.9034	2.1197
Age.C	0.2988	0.2230	1.3397	0.1804	-0.1375	0.7377	1.3482	0.8715	2.0912
GenderMale	1.5033	0.2134	7.0430	0	1.0888	1.9263	4.4965	2.9708	6.8642
Education.L	1.7761	0.5097	3.4844	0.0005	0.8008	2.8343	5.9068	2.2273	17.0186
Education.Q	-0.1526	0.3890	-0.3922	0.6949	-0.9010	0.6492	0.8585	0.4062	1.9139
Education.C	-0.2414	0.2289	-1.0546	0.2916	-0.6872	0.2161	0.7855	0.5030	1.2412
OccupationFinance job	1.6938	0.7394	2.2906	0.0220	0.2507	3.1699	5.4401	1.2849	23.8042
OccupationNon-finance job	0.0445	0.6432	0.0693	0.9448	-1.2198	1.3314	1.0456	0.2953	3.7862
OccupationFinance student	2.3649	0.7197	3.2862	0.0010	0.9586	3.7990	10.6435	2.6080	44.6552
OccupationNon-finance student	-0.0365	0.6928	-0.0527	0.9579	-1.3969	1.3407	0.9641	0.2474	3.8217
OccupationRetired	-0.6182	0.8291	-0.7457	0.4559	-2.2491	1.0217	0.5389	0.1055	2.7779
0|1	-3.6965	0.7305	-5.0601	0	NA	NA	NA	NA	NA
1|2	-1.9988	0.6668	-2.9977	0.0027	NA	NA	NA	NA	NA
2|3	-0.9124	0.6557	-1.3915	0.1641	NA	NA	NA	NA	NA
3|4	0.2955	0.6545	0.4515	0.6516	NA	NA	NA	NA	NA
4|5	2.0701	0.6630	3.1225	0.0018	NA	NA	NA	NA	NA

	Mc Fadden R2
llh	-525.9890
llhNull	-643.3044
G2	234.6307
McFadden	0.1824
r2ML	0.4358
r2CU	0.4555

	GVIF	Df	GVIF^(1/(2*Df))
Age	1.8852	3	1.1115
Gender	1.0803	1	1.0394
Education	1.1804	3	1.0280
Occupation	1.8622	5	1.0642

Stage 2: Impact of Financial Literacy on Investment Behavior

Asset Allocation

Savings Instruments

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	3.8401	213.6371	0.0180	0.9857	-3.0398	86.5549	46.5299	0.0478	3.89E+37
Financial_literacy_score	0.3578	0.1078	3.3186	0.0009	0.1482	0.5722	1.4302	1.1598	1.77E+00
Age.L	0.1839	0.3180	0.5781	0.5632	-0.4381	0.8158	1.2018	0.6452	2.26E+00
Age.Q	-0.0605	0.3023	-0.2001	0.8414	-0.6578	0.5322	0.9413	0.5180	1.70E+00
Age.C	0.0821	0.3146	0.2609	0.7941	-0.5363	0.7047	1.0856	0.5849	2.02E+00
GenderMale	-0.2123	0.2817	-0.7538	0.4510	-0.7674	0.3396	0.8087	0.4642	1.40E+00
Education.L	9.8024	573.2435	0.0171	0.9864	-38.7209	NA	18077.3455	0	NA
Education.Q	7.4903	427.2705	0.0175	0.9860	-31.1985	NA	1790.6756	0	NA
Education.C	3.2225	191.0812	0.0169	0.9865	-12.3042	NA	25.0915	0	NA
OccupationFinance job	1.3094	1.1332	1.1555	0.2479	-1.0219	3.6563	3.7038	0.3599	3.87E+01
OccupationNon-finance job	0.2407	0.8616	0.2794	0.7799	-1.7426	1.8076	1.2722	0.1751	6.10E+00
OccupationFinance student	-0.4991	0.9040	-0.5521	0.5808	-2.5417	1.1612	0.6070	0.0787	3.19E+00
OccupationNon-finance student	-0.9529	0.8931	-1.0670	0.2860	-2.9791	0.6846	0.3856	0.0508	1.98E+00
OccupationRetired	-1.3344	1.0875	-1.2270	0.2198	-3.6703	0.7094	0.2633	0.0255	2.03E+00

	Mc Fadden R2
llh	-202.8219
llhNull	-225.4806
G2	45.3174
McFadden	0.1005
r2ML	0.1046
r2CU	0.1569

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.6119	1	1.2696
Age	2.2231	3	1.1424
Gender	1.2827	1	1.1326
Education	1.2547	3	1.0385
Occupation	2.7404	5	1.1061

Stocks

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-3.8185	1.1959	-3.1931	0.0014	-6.8845	-1.7771	0.0220	0.0010	0.1691
Financial_literacy_score	0.5865	0.1323	4.4328	0	0.3365	0.8566	1.7977	1.4000	2.3552
Age.L	0.7986	0.2856	2.7964	0.0052	0.2459	1.3683	2.2223	1.2788	3.9286
Age.Q	-0.0415	0.2746	-0.1510	0.8800	-0.5809	0.4980	0.9594	0.5594	1.6454
Age.C	-0.4515	0.2848	-1.5855	0.1129	-1.0177	0.1016	0.6367	0.3614	1.1069
GenderMale	0.8374	0.2516	3.3280	0.0009	0.3461	1.3342	2.3104	1.4135	3.7971
Education.L	0.1581	0.6128	0.2580	0.7964	-1.0370	1.4348	1.1713	0.3545	4.1989
Education.Q	0.2735	0.4644	0.5889	0.5559	-0.6344	1.2355	1.3146	0.5303	3.4399
Education.C	-0.1446	0.2665	-0.5425	0.5875	-0.6665	0.3897	0.8654	0.5135	1.4766
OccupationFinance job	1.2806	1.1628	1.1013	0.2708	-0.6966	4.3065	3.5987	0.4983	74.1825
OccupationNon-finance job	0.6965	1.1068	0.6293	0.5291	-1.1368	3.6632	2.0068	0.3209	38.9877
OccupationFinance student	1.1906	1.1357	1.0483	0.2945	-0.7202	4.1873	3.2890	0.4867	65.8479
OccupationNon-finance student	0.1164	1.1715	0.0994	0.9208	-1.8959	3.1492	1.1235	0.1502	23.3183
OccupationRetired	0.9001	1.3120	0.6861	0.4927	-1.4629	4.0938	2.4598	0.2316	59.9679

	Mc Fadden R2
llh	-220.4729
llhNull	-267.5543
G2	94.1629
McFadden	0.1760
r2ML	0.2052
r2CU	0.2815

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5952	1	1.2630
Age	2.3160	3	1.1502
Gender	1.1738	1	1.0834
Education	1.3772	3	1.0548
Occupation	2.5127	5	1.0965

Bonds

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-3.2717	1.0864	-3.0114	0.0026	-5.6282	-1.2655	0.0379	0.0036	0.2821
Financial_literacy_score	0.6689	0.1692	3.9527	0.0001	0.3536	1.0199	1.9521	1.4242	2.7728
Age.L	1.1874	0.3392	3.5012	0.0005	0.5400	1.8751	3.2787	1.7160	6.5215
Age.Q	0.3707	0.3246	1.1422	0.2534	-0.2585	1.0183	1.4488	0.7722	2.7686
Age.C	-0.6941	0.3422	-2.0284	0.0425	-1.3871	-0.0385	0.4995	0.2498	0.9622
GenderMale	0.4918	0.3017	1.6300	0.1031	-0.0973	1.0887	1.6352	0.9073	2.9705
Education.L	1.1578	0.6681	1.7329	0.0831	-0.1914	2.4908	3.183	0.8258	12.0708
Education.Q	-0.6156	0.5065	-1.2154	0.2242	-1.6573	0.3686	0.5403	0.1907	1.4457
Education.C	-0.0306	0.2940	-0.1042	0.9170	-0.6184	0.5443	0.9698	0.5388	1.7235
OccupationFinance job	-0.3051	0.9976	-0.3058	0.7598	-2.1946	1.8668	0.7371	0.1114	6.4679
OccupationNon-finance job	-0.9321	0.9343	-0.9976	0.3185	-2.6762	1.1517	0.3937	0.0688	3.1637
OccupationFinance student	-1.7149	0.9856	-1.7399	0.0819	-3.5970	0.4291	0.1800	0.0274	1.5358
OccupationNon-finance student	-1.0736	1.0206	-1.0519	0.2929	-3.0338	1.1217	0.3418	0.0481	3.0701
OccupationRetired	-0.2177	1.2107	-0.1798	0.8573	-2.5793	2.2982	0.8043	0.0758	9.9561

	Mc Fadden R2
llh	-169.8250
llhNull	-214.5032
G2	89.3564
McFadden	0.2083
r2ML	0.1958
r2CU	0.3018

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5824	1	1.2579
Age	2.5263	3	1.1670
Gender	1.2265	1	1.1075
Education	1.3243	3	1.0479
Occupation	2.7295	5	1.1056

Mutual Funds

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-18.5718	793.5144	-0.0234	0.9813	NA	47.6399	0	NA	4.89E+20
Financial_literacy_score	0.6996	0.1919	3.6465	0.0003	0.3436	1.0991	2.0129	1.4100	3.00E+00
Age.L	1.9345	0.3959	4.8869	0	1.1955	2.7565	6.9205	3.3051	1.57E+01
Age.Q	0.1704	0.3712	0.4590	0.6462	-0.5453	0.9202	1.1858	0.5797	2.51E+00
Age.C	-1.0513	0.3949	-2.6624	0.0078	-1.8772	-0.3134	0.3495	0.1530	7.31E-01
GenderMale	0.7085	0.3441	2.0591	0.0395	0.0400	1.3932	2.0309	1.0408	4.03E+00
Education.L	0.8269	0.6890	1.2001	0.2301	-0.5024	2.2615	2.2862	0.6051	9.60E+00
Education.Q	0.7274	0.5240	1.3882	0.1651	-0.2946	1.8052	2.0696	0.7448	6.08E+00
Education.C	0.0940	0.3225	0.2914	0.7708	-0.5409	0.7338	1.0985	0.5822	2.08E+00
OccupationFinance job	15.1510	793.5142	0.0191	0.9848	-50.7627	NA	3802025.1204	0	NA
OccupationNon-finance job	14.1619	793.5141	0.0178	0.9858	-52.3647	NA	1413987.2146	0	NA
OccupationFinance student	13.6521	793.5143	0.0172	0.9863	-16.1925	297.3617	849282.4774	0	1.39E+129
OccupationNon-finance student	14.0317	793.5144	0.0177	0.9859	10.4343	326.6152	1241373.7511	34006.6767	7.03E+141
OccupationRetired	12.9703	793.5149	0.0163	0.9870	-17.1830	294.9888	429462.6430	0	1.29E+128

	Mc Fadden R2
llh	-139.0048
llhNull	-188.9601
G2	99.9107
McFadden	0.2644
r2ML	0.2163
r2CU	0.3591

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.6186	1	1.2722
Age	2.5178	3	1.1664
Gender	1.2406	1	1.1138
Education	1.4014	3	1.0579
Occupation	2.4047	5	1.0917

ETFs

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-28.0488	2044.7517	-0.0137	0.9891	-774.629	46.0266	0.00E+00	0	9.75E+19
Financial_literacy_score	1.2017	0.2992	4.017	0.0001	0.662	1.8393	3.33E+00	1.9386	6.29E+00
Age.L	-2.0988	0.6409	-3.2746	0.0011	-3.5424	-0.9573	1.23E-01	0.0289	3.84E-01
Age.Q	-1.2728	0.5533	-2.3002	0.0214	-2.4618	-0.2426	2.80E-01	0.0853	7.85E-01
Age.C	0.1164	0.4819	0.2416	0.8091	-0.8214	1.0874	1.12E+00	0.4398	2.97E+00
GenderMale	2.1873	0.4555	4.8018	0	1.348	3.1559	8.91E+00	3.8497	2.35E+01
Education.L	-11.6648	1465.5632	-0.008	0.9936	-566.4341	37.8413	0.00E+00	0	2.72E+16
Education.Q	-8.5999	1092.3663	-0.0079	0.9937	NA	81.0406	2.00E-04	NA	1.57E+35
Education.C	-3.8939	488.5211	-0.008	0.9936	-170.0093	16.0393	2.04E-02	0	9.24E+06
OccupationFinance job	16.1559	1970.4549	0.0082	0.9935	-62.7032	694.6333	1.04E+07	0	4.74E+301
OccupationNon-finance job	14.6688	1970.4548	0.0074	0.9941	-67.4123	675.4842	2.35E+06	0	2.29E+293
OccupationFinance student	15.285	1970.4548	0.0078	0.9938	-64.5871	688.2091	4.35E+06	0	7.68E+298
OccupationNon-finance student	15.1331	1970.4548	0.0077	0.9939	-62.7666	698.8694	3.73E+06	0	3.27E+303
OccupationRetired	1.858	2601.7328	0.0007	0.9994	-36.6123	40.1711	6.41E+00	0	2.79E+17

	Mc Fadden R2
llh	-105.4239
llhNull	-187.3883
G2	163.9286
McFadden	0.4374
r2ML	0.3296
r2CU	0.5501

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.2884	1	1.1351
Age	2.0921	3	1.1309
Gender	1.0327	1	1.0162
Education	1.4824	3	1.0678
Occupation	2.3827	5	1.0907

Real Estate

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-0.8580	0.9873	-0.8690	0.3849	-3.0286	0.9713	0.4240	0.0484	2.6414
Financial_literacy_score	0.1375	0.1174	1.1712	0.2415	-0.0900	0.3719	1.1474	0.9139	1.4505
Age.L	1.3218	0.3058	4.3224	0	0.7427	1.9480	3.7501	2.1016	7.0148
Age.Q	-1.1702	0.2755	-4.2475	0	-1.7199	-0.6368	0.3103	0.1791	0.5290
Age.C	-0.2227	0.2595	-0.8583	0.3907	-0.7386	0.2811	0.8003	0.4778	1.3246
GenderMale	-0.0571	0.2884	-0.1980	0.8431	-0.6242	0.5091	0.9445	0.5357	1.6637
Education.L	0.4940	0.5921	0.8343	0.4041	-0.6632	1.7270	1.6388	0.5152	5.6236
Education.Q	0.2045	0.4490	0.4554	0.6488	-0.6740	1.1353	1.2269	0.5096	3.1120
Education.C	-0.0146	0.2742	-0.0531	0.9576	-0.5526	0.5323	0.9855	0.5754	1.7028
OccupationFinance job	-0.2354	0.9887	-0.2381	0.8118	-2.0853	1.9289	0.7902	0.1243	6.8819
OccupationNon-finance job	-0.0679	0.9131	-0.0744	0.9407	-1.7571	1.9833	0.9343	0.1725	7.2670
OccupationFinance student	-1.5774	1.1021	-1.4313	0.1523	-3.7310	0.7483	0.2065	0.0240	2.1133
OccupationNon-finance student	-1.1574	1.0915	-1.0604	0.2890	-3.2966	1.1468	0.3143	0.0370	3.1483
OccupationRetired	0.3103	1.1056	0.2807	0.7789	-1.8026	2.6566	1.3639	0.1649	14.2477

	Mc Fadden R2
llh	-193.0194
llhNull	-244.2355
G2	102.4322
McFadden	0.2097
r2ML	0.2211
r2CU	0.3175

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5560	1	1.2474
Age	1.6396	3	1.0859
Gender	1.2949	1	1.1379
Education	1.3329	3	1.0491
Occupation	1.8792	5	1.0651

Derivatives

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-21.6150	2149.2102	-0.0101	0.9920	-726.9728	70.7228	0	0	5.18E+30
Financial_literacy_score	0.8486	0.4070	2.0852	0.0371	0.1393	1.7430	2.3363	1.1495	5.71E+00
Age.L	0.5908	0.5165	1.1440	0.2526	-0.4024	1.6456	1.8055	0.6687	5.18E+00
Age.Q	0.0939	0.5056	0.1858	0.8526	-0.8853	1.1152	1.0985	0.4126	3.05E+00
Age.C	0.0971	0.5338	0.1818	0.8557	-0.9560	1.1803	1.1019	0.3844	3.26E+00
GenderMale	1.6736	0.6610	2.5318	0.0113	0.5036	3.1792	5.3312	1.6547	2.40E+01
Education.L	0.6858	1.1073	0.6193	0.5357	-1.7142	3.0677	1.9853	0.1801	2.15E+01
Education.Q	-0.5237	0.8394	-0.6238	0.5327	-2.4836	0.9619	0.5923	0.0834	2.62E+00
Education.C	0.1469	0.4769	0.3080	0.7581	-0.8314	1.1140	1.1582	0.4355	3.05E+00
OccupationFinance job	14.9382	2149.2097	0.0070	0.9945	-88.4045	659.9723	3072956.5546	0	4.19E+286
OccupationNon-finance job	14.0010	2149.2097	0.0065	0.9948	-91.7751	645.6961	1203792.4577	0	2.64E+280
OccupationFinance student	13.9015	2149.2097	0.0065	0.9948	-96.0033	622.9646	1089759.7095	0	3.55E+270
OccupationNon-finance student	13.4735	2149.2099	0.0063	0.9950	-101.2838	349.0527	710336.3402	0	3.91E+151
OccupationRetired	-0.8422	2798.7854	-0.0003	0.9998	-61.8060	61.5282	0.4307	0	5.26E+26

	Mc Fadden R2
llh	-73.6941
llhNull	-99.5394
G2	51.6907
McFadden	0.2596
r2ML	0.1185
r2CU	0.3079

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.3831	1	1.1761
Age	2.0184	3	1.1242
Gender	1.0861	1	1.0421
Education	1.3567	3	1.0522
Occupation	2.2374	5	1.0839

Commodities

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-18.5208	1334.6814	-0.0139	0.9889	NA	88.9337	0	NA	4.20E+38
Financial_literacy_score	0.3393	0.2384	1.4234	0.1546	-0.0963	0.8474	1.4040	0.9082	2.33E+00
Age.L	0.2432	0.4799	0.5068	0.6123	-0.6875	1.2173	1.2753	0.5028	3.38E+00
Age.Q	-0.5424	0.4423	-1.2265	0.2200	-1.4172	0.3315	0.5813	0.2424	1.39E+00
Age.C	0.6839	0.4305	1.5887	0.1121	-0.1386	1.5745	1.9817	0.8706	4.83E+00
GenderMale	0.6238	0.4612	1.3525	0.1762	-0.2642	1.5589	1.8661	0.7678	4.75E+00
Education.L	0.9836	1.0487	0.9379	0.3483	-1.3209	3.2868	2.6740	0.2669	2.68E+01
Education.Q	-1.0978	0.7845	-1.3993	0.1617	-2.9851	0.2509	0.3336	0.0505	1.29E+00
Education.C	0.1116	0.4402	0.2534	0.7999	-0.7990	1.0195	1.1180	0.4498	2.77E+00
OccupationFinance job	14.8541	1334.6812	0.0111	0.9911	-52.9208	395.7039	2825244.8852	0	7.11E+171
OccupationNon-finance job	14.0096	1334.6812	0.0105	0.9916	-47.8133	427.4853	1214178.7276	0	4.51E+185
OccupationFinance student	13.1979	1334.6813	0.0099	0.9921	-50.6054	415.8183	539228.3726	0	3.87E+180
OccupationNon-finance student	14.3610	1334.6813	0.0108	0.9914	-50.1626	413.0329	1725464.1152	0	2.39E+179
OccupationRetired	-0.1291	1749.8582	-0.0001	0.9999	-35.0637	35.9021	0.8789	0	3.91E+15

	Mc Fadden R2
llh	-90.8416
llhNull	-109.8446
G2	38.0061
McFadden	0.1730
r2ML	0.0885
r2CU	0.2134

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.4747	1	1.2144
Age	1.7821	3	1.1011
Gender	1.2352	1	1.1114
Education	1.2456	3	1.0373
Occupation	2.0537	5	1.0746

Cryptocurrency

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-19.8546	1277.0002	-0.0155	0.9876	NA	87.0721	0	NA	6.53E+37
Financial_literacy_score	0.5078	0.1646	3.0858	0.0020	0.1991	0.8469	1.6617	1.2203	2.33E+00
Age.L	-0.8652	0.3979	-2.1743	0.0297	-1.7037	-0.1200	0.4210	0.1820	8.87E-01
Age.Q	-1.0001	0.3568	-2.8034	0.0051	-1.7321	-0.3211	0.3678	0.1769	7.25E-01
Age.C	-0.7185	0.3236	-2.2202	0.0264	-1.3637	-0.0902	0.4875	0.2557	9.14E-01
GenderMale	1.5277	0.3177	4.8080	0	0.9207	2.1711	4.6077	2.5109	8.77E+00
Education.L	-0.5733	0.8279	-0.6925	0.4886	-2.6547	0.8769	0.5636	0.0703	2.40E+00
Education.Q	-0.4059	0.6287	-0.6456	0.5185	-1.9731	0.6924	0.6664	0.1390	2.00E+00
Education.C	-0.3259	0.3395	-0.9600	0.3371	-1.1008	0.2988	0.7219	0.3326	1.35E+00
OccupationFinance job	15.0976	1277.0001	0.0118	0.9906	-90.6989	NA	3604057.6777	0	NA
OccupationNon-finance job	15.5007	1277.0001	0.0121	0.9903	-92.0607	NA	5393262.6170	0	NA
OccupationFinance student	15.4497	1277.0001	0.0121	0.9903	-91.3255	NA	5125355.5021	0	NA
OccupationNon-finance student	15.0615	1277.0001	0.0118	0.9906	-72.3878	NA	3476438.1457	0	NA
OccupationRetired	0.9681	1677.3083	0.0006	0.9995	-16.8335	19.3427	2.6328	0	2.51E+08

	Mc Fadden R2
llh	-167.1442
llhNull	-213.2132
G2	92.1380
McFadden	0.2161
r2ML	0.2013
r2CU	0.3113

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5561	1	1.2474
Age	1.8718	3	1.1101
Gender	1.1847	1	1.0885
Education	1.4317	3	1.0616
Occupation	2.2156	5	1.0828

Collectibles

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-2.3748	1.3292	-1.7866	0.0740	-5.6172	-0.0603	0.0930	0.0036	0.9415
Financial_literacy_score	0.0754	0.2074	0.3637	0.7161	-0.3148	0.5054	1.0783	0.7300	1.6576
Age.L	-0.3792	0.4333	-0.8752	0.3815	-1.2546	0.4673	0.6844	0.2852	1.5957
Age.Q	0.4076	0.4760	0.8563	0.3918	-0.5022	1.3944	1.5032	0.6052	4.0324
Age.C	0.4240	0.5164	0.8212	0.4116	-0.5583	1.5318	1.5281	0.5722	4.6264
GenderMale	0.3827	0.4444	0.8612	0.3891	-0.4811	1.2746	1.4662	0.6181	3.5774
Education.L	0.7490	0.8670	0.8639	0.3876	-1.3774	2.3063	2.1150	0.2522	10.0376
Education.Q	0.1984	0.6550	0.3029	0.7620	-1.4000	1.3652	1.2194	0.2466	3.9164
Education.C	-0.2250	0.4086	-0.5506	0.5819	-1.1064	0.5449	0.7985	0.3307	1.7244
OccupationFinance job	-0.0654	1.2520	-0.0522	0.9584	-2.2851	3.0559	0.9367	0.1018	21.2403
OccupationNon-finance job	-0.5533	1.1591	-0.4774	0.6331	-2.5140	2.4703	0.5750	0.0809	11.8256
OccupationFinance student	-1.1238	1.2361	-0.9092	0.3633	-3.3251	1.9759	0.3250	0.0360	7.2134
OccupationNon-finance student	-2.1317	1.4974	-1.4236	0.1546	-5.4773	1.2054	0.1186	0.0042	3.3379
OccupationRetired	0.0139	1.6167	0.0086	0.9931	-3.4865	3.5385	1.0140	0.0306	34.4146

	Mc Fadden R2
llh	-98.3653
llhNull	-104.7663
G2	12.8021
McFadden	0.0611
r2ML	0.0307
r2CU	0.0768

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.7071	1	1.3066
Age	1.7442	3	1.0971
Gender	1.2570	1	1.1212
Education	1.4611	3	1.0652
Occupation	2.4158	5	1.0922

No Investment

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-5.3131	547.8215	-0.0097	0.9923	-201.8804	15.1629	0.0049	0	3.85E+06
Financial_literacy_score	-0.3181	0.1279	-2.4866	0.0129	-0.5718	-0.0681	0.7275	0.5645	9.34E-01
Age.L	-0.6343	0.4094	-1.5493	0.1213	-1.4610	0.1601	0.5303	0.2320	1.17E+00
Age.Q	0.9503	0.4530	2.0979	0.0359	0.0965	1.9021	2.5866	1.1013	6.70E+00
Age.C	0.4984	0.5188	0.9607	0.3367	-0.4889	1.6105	1.6462	0.6133	5.01E+00
GenderMale	-0.8066	0.3826	-2.1085	0.0350	-1.5836	-0.0743	0.4464	0.2052	9.28E-01
Education.L	-10.4408	1469.956	-0.0071	0.9943	NA	140.4275	0	NA	9.70E+60
Education.Q	-7.7904	1095.6405	-0.0071	0.9943	NA	104.0402	0.0004	NA	1.53E+45
Education.C	-3.1985	489.9854	-0.0065	0.9948	-174.0439	16.0223	0.0408	0	9.09E+06
OccupationFinance job	-15.1375	1002.7931	-0.0151	0.9880	-390.9404	19.4280	0	0	2.74E+08
OccupationNon-finance job	0.2702	1.1387	0.2373	0.8125	-1.6312	3.2732	1.3102	0.1957	2.64E+01
OccupationFinance student	0.6880	1.1913	0.5776	0.5636	-1.3513	3.7469	1.9898	0.2589	4.24E+01
OccupationNon-finance student	1.4574	1.1565	1.2601	0.2076	-0.4958	4.4782	4.2949	0.6091	8.81E+01
OccupationRetired	-0.0476	1.5897	-0.0300	0.9761	-3.5141	3.4308	0.9535	0.0298	3.09E+01

	Mc Fadden R2
llh	-130.0942
llhNull	-157.8473
G2	55.5062
McFadden	0.1758
r2ML	0.1266
r2CU	0.2358

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.4488	1	1.2036
Age	1.8083	3	1.1038
Gender	1.1649	1	1.0793
Education	1.2075	3	1.0319
Occupation	2.1106	5	1.0776

Active versus Passive Investment Strategy

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
(Intercept)	-2.0000	1.0178	-1.9649	0.0494	-4.2224	-0.1017	0.1353	0.0147	0.9033
Financial_literacy_score	0.2796	0.1470	1.9025	0.0571	0.0004	0.5788	1.3226	1.0004	1.7840
Age.L	0.2804	0.3067	0.9143	0.3606	-0.3183	0.8894	1.3236	0.7274	2.4338
Age.Q	0.1309	0.3111	0.4209	0.6738	-0.4737	0.7510	1.1399	0.6227	2.1191
Age.C	-0.6994	0.3263	-2.1438	0.0321	-1.3647	-0.0766	0.4969	0.2554	0.9262
GenderMale	0.3348	0.2986	1.1212	0.2622	-0.2484	0.9256	1.3977	0.7801	2.5233
Education.L	0.3019	0.6464	0.4671	0.6404	-1.1172	1.5299	1.3525	0.3272	4.6175
Education.Q	0.0335	0.4931	0.0679	0.9458	-1.0444	0.9653	1.0341	0.3519	2.6254
Education.C	-0.1562	0.2902	-0.5383	0.5903	-0.7542	0.4012	0.8554	0.4704	1.4936
OccupationFinance job	-0.4462	0.9570	-0.4662	0.6411	-2.2470	1.6642	0.6401	0.1057	5.2817
OccupationNon-finance job	-0.3849	0.8840	-0.4354	0.6633	-2.0197	1.6257	0.6805	0.1327	5.0819
OccupationFinance student	-0.6222	0.9345	-0.6658	0.5055	-2.3807	1.4531	0.5368	0.0925	4.2765
OccupationNon-finance student	-1.9426	1.1360	-1.7101	0.0872	-4.3053	0.3838	0.1433	0.0135	1.4679
OccupationRetired	0.3011	1.1517	0.2614	0.7938	-1.9527	2.7094	1.3513	0.1419	15.0209

	Mc Fadden R2
llh	-180.0237
llhNull	-191.4446
G2	22.8418
McFadden	0.0597
r2ML	0.0610
r2CU	0.0936

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.6932	1	1.3012
Age	2.1368	3	1.1349
Gender	1.3035	1	1.1417
Education	1.3805	3	1.0552
Occupation	2.6323	5	1.1016

Investment Horizon Preferences

	Estimate	Std.Error	t value	p value	CI Lower	CI Upper
Financial_literacy_score	0.0562	0.0586	0.9600	0.3371	-0.0587	0.1709
Age.L	0.1914	0.1472	1.2998	0.1937	-0.0969	0.4804
Age.Q	-0.0195	0.1416	-0.1378	0.8904	-0.2974	0.2579
Age.C	0.1167	0.1429	0.8167	0.4141	-0.1631	0.3971
GenderMale	0.0354	0.1384	0.2557	0.7982	-0.2360	0.3068
Education.L	-0.1120	0.3266	-0.3428	0.7317	-0.7427	0.5419
Education.Q	-0.1689	0.2473	-0.6831	0.4945	-0.6472	0.3252
Education.C	-0.1626	0.1427	-1.1388	0.2548	-0.4406	0.1196
OccupationFinance job	0.4411	0.4936	0.8937	0.3715	-0.5359	1.4017
OccupationNon-finance job	-0.0163	0.4472	-0.0364	0.9709	-0.9073	0.8491
OccupationFinance student	0.0082	0.4701	0.0174	0.9861	-0.9241	0.9210
OccupationNon-finance student	0.1246	0.4772	0.2611	0.7940	-0.8216	1.0516
OccupationRetired	-0.6624	0.5684	-1.1653	0.2439	-1.7863	0.4441
Short term|Medium term	-1.1804	0.4948	-2.3858	0.0170	NA	NA
Medium term|Long term	0.2187	0.4903	0.4460	0.6556	NA	NA

	Mc Fadden R2
llh	-328.2600
llhNull	-336.3546
G2	16.1892
McFadden	0.0241
r2ML	0.0426
r2CU	0.0509

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5748	1	1.2549
Age	2.0715	3	1.1290
Gender	1.2776	1	1.1303
Education	1.3205	3	1.0474
Occupation	2.4207	5	1.0924

Risk Tolerance

	Estimate	Std.Error	z value	p value	CI_lower	CI_upper	OddsRatio	OR_CI_lower	OR_CI_upper
Financial_literacy_score	0.1548	0.0833	1.8590	0.0630	-0.0078	0.3190	1.1674	0.9922	1.3758
Age.L	-0.7977	0.2198	-3.6284	0.0003	-1.2308	-0.3683	0.4504	0.2921	0.6919
Age.Q	0.1574	0.2105	0.7480	0.4544	-0.2551	0.5706	1.1705	0.7749	1.7694
Age.C	-0.3142	0.2180	-1.4408	0.1496	-0.7425	0.1131	0.7304	0.4759	1.1198
GenderMale	1.0534	0.2099	5.0178	0	0.6448	1.4683	2.8673	1.9055	4.3420
Education.L	0.3339	0.4861	0.6870	0.4921	-0.6242	1.3001	1.3965	0.5357	3.6698
Education.Q	0.0960	0.3676	0.2612	0.7939	-0.6258	0.8289	1.1008	0.5348	2.2909
Education.C	-0.0537	0.2094	-0.2566	0.7975	-0.4641	0.3599	0.9477	0.6287	1.4333
OccupationFinance job	1.1848	0.7874	1.5048	0.1324	-0.3600	2.7681	3.2702	0.6976	15.9282
OccupationNon-finance job	0.4699	0.723	0.6500	0.5157	-0.9494	1.9378	1.5999	0.3870	6.9438
OccupationFinance student	0.4189	0.7434	0.5635	0.5731	-1.0393	1.9213	1.5202	0.3537	6.8301
OccupationNon-finance student	0.2181	0.7468	0.2921	0.7702	-1.2442	1.7292	1.2437	0.2882	5.6363
OccupationRetired	1.0373	0.9433	1.0996	0.2715	-0.8183	2.9125	2.8216	0.4412	18.4034
Very risk-averse|Somewhat risk-averse	-0.1051	0.7781	-0.1351	0.8925	NA	NA	NA	NA	NA
Somewhat risk-averse|Neutral	1.3766	0.7791	1.7669	0.0772	NA	NA	NA	NA	NA
Neutral|Somewhat risk-tolerant	2.8689	0.7887	3.6377	0.0003	NA	NA	NA	NA	NA
Somewhat risk-tolerant|Very risk-tolerant	5.0168	0.8228	6.0970	0	NA	NA	NA	NA	NA

	Mc Fadden R2
llh	-566.4678
llhNull	-612.1470
G2	91.3585
McFadden	0.0746
r2ML	0.1997
r2CU	0.2104

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5155	1	1.2311
Age	2.0094	3	1.1233
Gender	1.2226	1	1.1057
Education	1.3491	3	1.0512
Occupation	2.5277	5	1.0972

Trading Frequency

	Estimate	Std.Error	t value	p value	CI Lower	CI Upper
Financial_literacy_score	0.1435	0.0522	2.7499	0.0060	0.0416	0.2463
Age.L	0.0988	0.1295	0.7629	0.4455	-0.1549	0.3529
Age.Q	-0.0421	0.1265	-0.3327	0.7394	-0.2899	0.2059
Age.C	-0.2020	0.1307	-1.5449	0.1224	-0.4585	0.0540
GenderMale	0.7066	0.1242	5.6882	0	0.4634	0.9503
Education.L	-0.0797	0.2957	-0.2697	0.7874	-0.6609	0.4988
Education.Q	0.2013	0.2241	0.8987	0.3688	-0.2389	0.6398
Education.C	-0.0725	0.1277	-0.5675	0.5704	-0.3232	0.1775
OccupationFinance job	0.0598	0.4425	0.1351	0.8925	-0.8006	0.9356
OccupationNon-finance job	0.0435	0.4066	0.1070	0.9148	-0.7448	0.8515
OccupationFinance student	0.1514	0.4275	0.3541	0.7233	-0.6789	0.9990
OccupationNon-finance student	-0.1202	0.4298	-0.2796	0.7798	-0.9550	0.7320
OccupationRetired	-0.1430	0.5306	-0.2695	0.7876	-1.1805	0.9010
Never|Rarely	0.4075	0.4410	0.9240	0.3555	NA	NA
Rarely|Annually	1.4322	0.4457	3.2134	0.0013	NA	NA
Annually|Monthly	1.4810	0.4460	3.3203	0.0009	NA	NA
Monthly|Weekly	2.3803	0.4530	5.2550	0	NA	NA
Weekly|Daily	2.8668	0.4589	6.2469	0	NA	NA

	Mc Fadden R2
llh	-526.3324
llhNull	-563.4480
G2	74.2313
McFadden	0.0659
r2ML	0.1656
r2CU	0.1769

	GVIF	Df	GVIF^(1/(2*Df))
Financial_literacy_score	1.5746	1	1.2548
Age	2.0009	3	1.1225
Gender	1.2345	1	1.1111
Education	1.3435	3	1.0504
Occupation	2.4661	5	1.0945

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Statement on the Use of Artificial Intelligence

In line with the ULiège Charter on the Use of Generative Artificial Intelligence, I declare that Artificial Intelligence tools (such as ChatGPT) were used during the preparation of this thesis. These tools were employed primarily as linguistic aids to enhance the clarity, coherence, and syntax of texts that I personally authored.

Additionally, and following the guidance of Professor Caterina Santi, AI-based tools were employed to assist with specific programming and coding tasks. This included technical support such as code debugging, optimization, and clarification of programming concepts. At no point were content generation, critical analysis, or the development of arguments entrusted to artificial intelligence. I take full responsibility for the intellectual content of this work.

EXECUTIVE SUMMARY

This thesis investigates the interplay between financial literacy, demographic characteristics, and investment behavior among Belgian adults aged 18 to 65. In an era of increasing financial complexity, financial literacy—defined as the ability to acquire, comprehend, and apply financial knowledge—has become vital for sound investment decision-making. Despite growing global attention to its importance, the mechanisms by which financial literacy influences investment behavior remain underexplored in the Belgian context. This study addresses this gap by examining the effects of demographic variables on financial literacy and, in turn, the role of financial literacy in shaping individual investment behaviors.

Empirical findings reveal significant demographic disparities: men, individuals with higher education levels, and those with academic or professional finance exposure exhibit higher financial literacy. Contrary to life-cycle model expectations, age was not a significant predictor. The analysis further indicates that financial literacy is positively linked to diversified asset allocation and increased trading frequency—potentially reflecting overconfidence. It also shows marginal positive effects on risk tolerance and engagement in active investment strategies, though no clear pattern emerged regarding long-term investment horizon preferences.

These results underscore the dual role of financial literacy: it fosters informed, diversified investment choices but may also contribute to excessive trading. The persistence of financial literacy gaps across demographics highlights the need for targeted educational initiatives. Policy recommendations include integrating financial literacy into formal education and creating behaviorally informed programs to mitigate cognitive biases and promote financial inclusion.

While offering meaningful insights, the study's generalizability is limited by methodological constraints. Future research should adopt more robust methodologies and consider behavioral mediators to clarify how financial literacy shapes investment behavior. Ultimately, this thesis provides a nuanced understanding of financial literacy as both an enabler of prudent investing and a potential driver of suboptimal behaviors in the Belgian context.

KEYWORDS: Financial Literacy, Investment Behavior, Demographic Characteristics, Belgian Adults, Asset Allocation, Portfolio Diversification, Active versus Passive Investment Strategy, Investment Horizon, Risk Tolerance, Trading Frequency, Cognitive Biases, Financial Education, Financial Inclusion, Educational Initiatives.

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