Università degli Studi di Milano-Bicocca

Data Science Lab

Final Essay

Understanding Financial Literacy in Italy: Socio-economic Implications and Policy Insights

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Abstract

This study explores the landscape of financial literacy (FL) in Italy across the years 2017, 2020, and 2023, examining its variations among different socio-demographic groups. Leveraging datasets from the Bank of Italy, the analysis employs both unsupervised and supervised analyzes through Self-Organizing Map technique in order to assess how FL is decomposed and how socio-demographic factors could influence it. The research aims to uncover insights into the role of FL in shaping economic disparities and potential socio-economic divisions. Key findings highlight distinct patterns in financial attitudes, knowledge, and behaviors, emphasizing the need for targeted educational initiatives to enhance FL among diverse demographic segments. The study underscores the significance of strengthening financial literacy education as Italy prepares to integrate enhanced financial preparedness strategies.

1 Introduction

The term ”financial literacy” was defined by the Jump$tart Coalition for Personal Financial Literacy in 1997 as ”the ability to use knowledge and skills to manage one’s financial resources effectively for lifetime financial security” [Mandell, 2008].

Over time, subsequent definitions have expanded on this initial conceptualization. For instance, in 2012, the Organization for Economic Cooperation and Development (OECD) defined financial literacy as ”the knowledge and understanding of financial concepts and risks, and the skills, motivation, and confidence to apply such knowledge and understanding in order to make effective decisions across a range of financial contexts, to improve the financial well-being of individuals and society, and to enable participation in economic life” [OECD, 2017]. This definition highlights knowledge and behavior as key components of financial literacy, while also recognizing the importance of understanding and managing risk.

Empirical evidences link financial literacy with economic stability and prudent financial behavior [Lusardi and Messy, 2023]. Research indicates that an individual’s ability to understand and use basic financial and economic concepts plays a crucial role in attaining financial stability and security [Banca d’Italia, n.d]. Conversely, there is a documented negative correlation between financial literacy and errors in financial decision-making: individuals with lower levels of financial literacy are more likely to make sub optimal financial decisions. Notably, evidences suggest that low financial literacy is associated with high-cost borrowing and poor mortgage choices [Lusardi and Tufano, 2015, Moore, 2003].

The OECD’s broader definition views financial literacy as a multidimensional construct comprising three main dimensions: financial knowledge, financial behavior, and financial attitude. This framework was the basis for several studies [Potrich et al., 2015, Atkinson and Messy, 2012].

Financial knowledge refers to the ability to manage income, expenditures, and savings in an efficient manner. Financial attitude, as described by Shockey [2002], relates to the predisposition to act favorably in financial matters. And finally, financial behavior is a critical aspect of an individual’s life and refers to how a person manages their money, makes financial decisions, and deals with financial issues.

This study examines the state of art of financial literacy in Italy, utilizing data from surveys conducted in 2017, 2020, and 2023 through the OECD/INFE questionnaire.

The analysis focuses on assessing variations in financial attitude, knowledge, and behavior across different socio-demographic groups within Italy. By employing clustering techniques, the research aims to uncover insights into how FL subdimension values spread across population, and how socio-demographic factors influence financial literacy levels. Understanding these dynamics is crucial for formulating targeted policies to enhance financial education and preparedness in Italy.

To provide context, the following section will explore the economic indicators and methodology used, highlighting the link between Italy’s economic landscape and the observed trends of financial literacy among its population.

2 Economic Context

Italy's economic landscape has undergone significant changes over the past decade, influencing the financial literacy and behaviors of its citizens. Several key economic indicators provide insight into the financial environment in which Italian households operate.

2.1 Gross Domestic Product

The Gross Domestic Product (GDP) growth rate is a crucial indicator of a country's economic health, reflecting the expansion rate of its economy. A positive GDP growth rate is generally seen as a sign of a healthy economy. According to Mankiw [2019], GDP growth, encompassing the total value of goods and services produced within a country over a specific period, is a primary measure of economic performance.

Sustained GDP growth indicates robust economic activity, often translating into higher employment rates, increased consumer spending, and greater investments in infrastructure and technology. Collectively, these factors improve a State's overall financial health. For example, Barro and i Martin [2004] argue that GDP growth is linked to improvements in living standards, as it often leads to higher incomes and better access to resources.

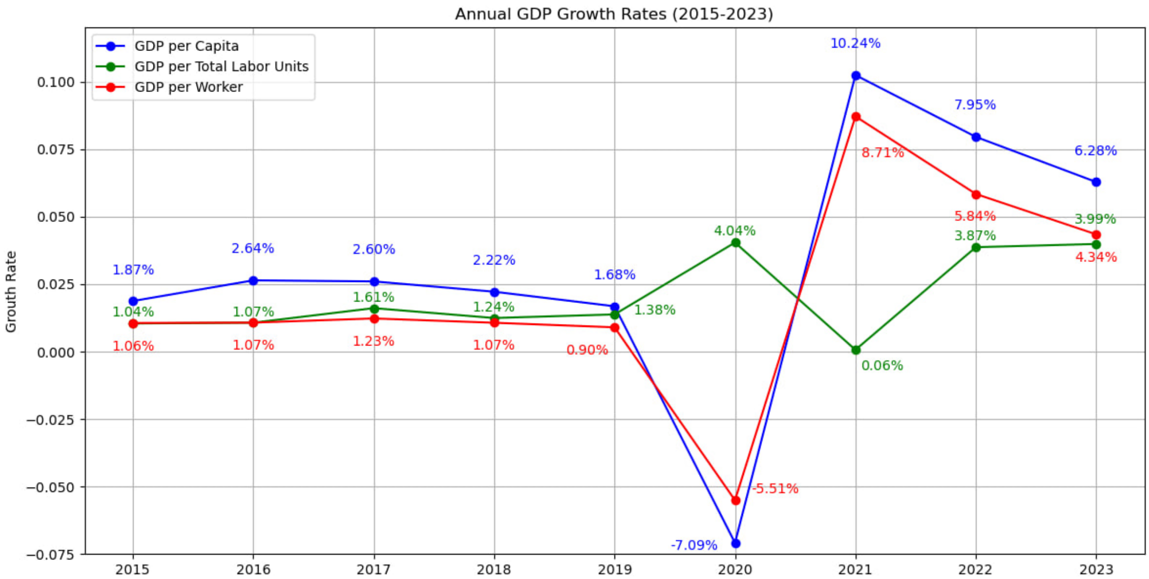


Figure 1: Annual GDP Growth Rates in Italy (2015-2023), divided by GDP per Capita, GDP per Total Work Unit, and GDP per Employed Person.

Figure 1 displays Italy's GDP growth rates from 2015 to 2023, highlighting significant economic trends. GDP per capita, GDP per total labor unit, and GDP per employed person each reflect varying impacts of economic events. From 2015 to 2019, moderate growth indicates steady economic progress. The sharp decline in 2020 across all measures reflects the severe impact of COVID-19, followed by significant recoveries in 2021 due to economic stimulus and reopening. Subsequent declines in 2022 and 2023 suggest stabilization at lower growth rates.

2.2 Consumer Prices

The Consumer Price Index (CPI) measures the average change over time in prices paid by consumers for a basket of goods and services. It is used to observe inflationary trends and assess the cost of living [Bureau of Labor Statistics, 2022, Diewert, 2020].

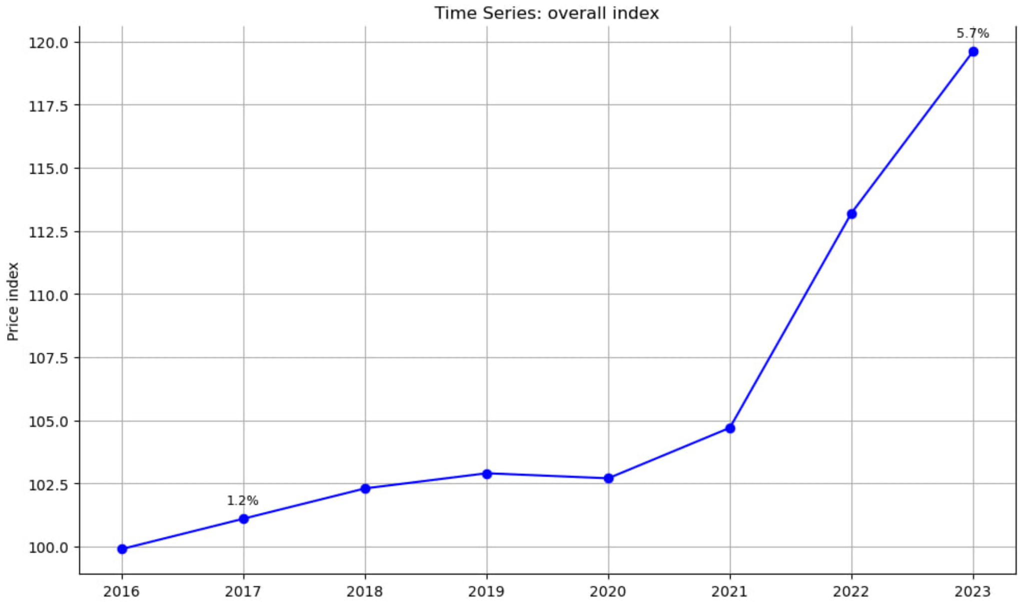


Figure 2: Time Series of the overall Price index (2016-2023). The price index is a statistical measure used to track changes in the price level of a basket of goods and services over time. A price index can represent inflation, the cost of living, or other significant economic changes (OECD,2023)

Figure 2 shows a steady upward trend in the general CPI index from 99.9 in 2016 to 119.6 in 2023. Notably, the inflation rate surges significantly in 2022 (+8.1%) and remains elevated in 2023 (+5.7%). These increases suggest heightened inflationary pressures, influenced by factors such as supply chain disruptions and post-pandemic demand recovery.

Drilling down into specific sectors, Figure 3 illustrates the inflation trends across food, housing and utilities, health services, and transportations. Food expenditure shows gradual increases with notable spikes in 2022 (+8.6%) and 2023 (+5.3%). Housing and utilities demonstrate consistent growth, notably peaking in 2022 (+9%) and 2023 (+5.5%), indicating rising energy expenses and housing market dynamics. Health services faced substantial inflationary pressures, peaking at +10.1% in 2022 and +6.4% in 2023. While transport costs reflect moderate inflation linked to fuel price fluctuations, with a peak of +1.7% in 2023.

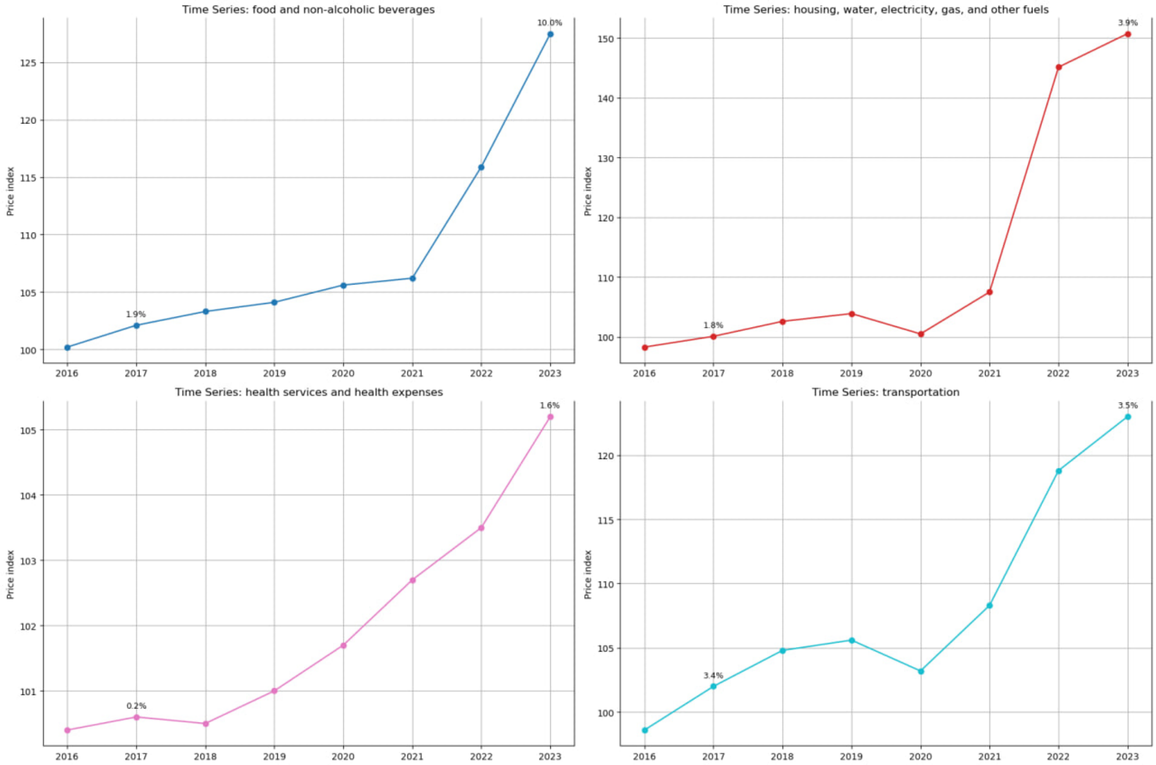


Figure 3: Time Series of Price indices regarding the main daily needs (2016-2023)

These sectoral analyses underscore varied economic pressures contributing to overall consumer price increases, highlighting distinct sector-specific dynamics impacting inflation trends.

2.3 Household Disposable Income

Household disposable income is a key factor in exploring the financial wellness of a country.
Figure 4 shows Italy's gross household income from 2014 to 2023, values refer to the overall gross household income, scaled in millions of Euros. After a steady increase from €1,070.03 billion in 2014 to around €1,120.00 billion in 2019, there was a notable dip in 2020 to €1,094.58 billion due to the economic impact of the COVID-19 pandemic [OECD, 2022]. A subsequent rebound in 2021 indicates economic recovery efforts, while slight declines in 2022 and 2023 suggest ongoing economic challenges, possibly due to inflationary pressures and global economic uncertainties [International Monetary Fund, 2023].

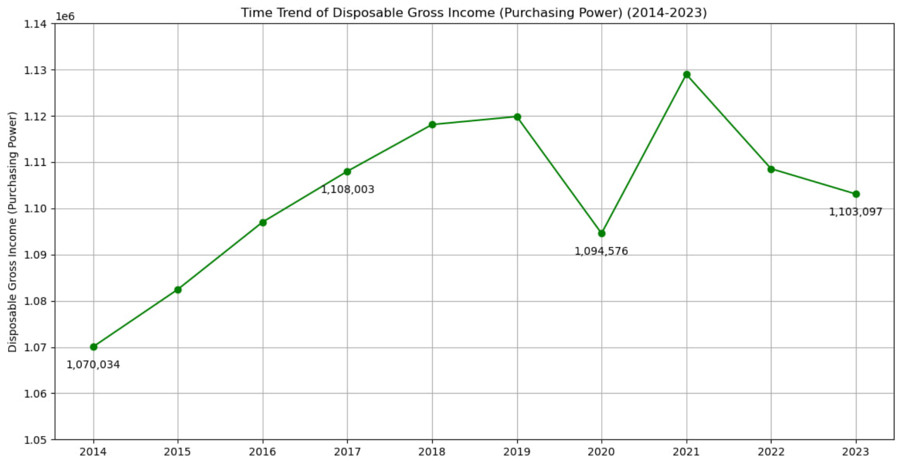


Figure 4: Time Series of disposable gross income with a rapid growth from 2014 to 2019, followed by a dip to 1,094,576 in 2020, a peak at 1,130,000 in 2021, and then a gradual decline to 1,103,097 in 2023.

The gross savings rate, representing the percentage of income saved, also reflects economic challenges. Figure 5 shows a trend from 2014 to 2023, that highlights a challenging scenario due to a slight breakdown (6.3% in 2023) after a steady but short decrease from 2014 to 2018 (gross saving rate ranged from 9.0% to 8.0%) as the effect of stable economic growth Eurostat [2024], while the rapid increase to 15.6% in 2020 resulted from precautionary savings due to the COVID-19 pandemic, as households prioritized financial security amidst uncertainty Organisation for Economic Co-operation and Development [2023]. The subsequent decrease in 2021 and 2022, to 13.6% and 7.8% respectively, suggests a return to pre-pandemic levels but with ongoing economic challenges affecting savings behaviors International Monetary Fund [2022]. The decline to 6.3% in 2023 indicates persistent economic vulnerability.

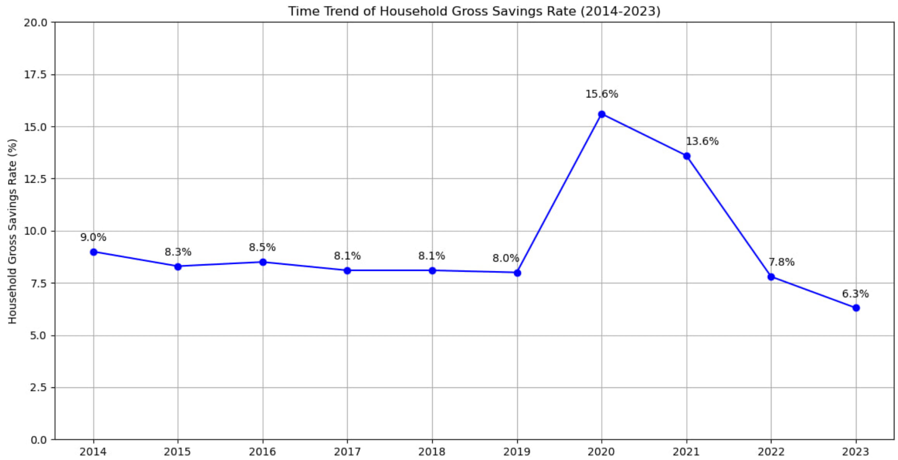


Figure 5: Time Series of the household gross savings rate from 2014 to 2023, highlighting a significant peak at 15.6% in 2020, followed by a gradual decline to 6.3% in 2023.

These trends certainly suggest the importance of policy measures to support household financial resilience and economic stability.

3 Data Collection and Preprocessing

In order to investigate the phenomenon of financial literacy in Italy, data sourced from the Bank of Italy's official website (`https://www.bancaditalia.it/`) were utilized. The Bank of Italy has conducted three comprehensive surveys on this topic at distinct intervals: 2017, 2020, and 2023. In 2017, the survey involved 2,376 individuals, providing a foundational dataset for understanding financial literacy at that time. Subsequent surveys in 2020 and 2023 were conducted with samples of 2,036 and 4,862 subjects respectively, drawn from the general population. The surveys utilized the OECD/INFE questionnaire (see Appendix D), which evolved over time to assess financial knowledge, attitudes, and behaviors.

3.1 Pre-processing

Over the years, the survey questionnaires underwent several modifications, including the addition of demographic variables, minor changes in question wording, and adjustments in response options. Our preprocessing strategy aimed to standardize these changes across survey years while focusing on common demographic variables. Ultimately, we retained gender (male, female), age groups (18-29, 30-39, 40-49, 50-59, 60-69, 70+), geographical area (Centre, Islands, North East, North West, South), educational qualification (High School, Middle School, University Level, No Education, Primary School, Other), and employment status (Employed, Retired, Self-Employed, Student, Homemaker, Unemployed, Other). The final sample distribution across survey years is detailed in Table 1, showing the frequency and percentage of respondents within each demographic category for 2017, 2020, and 2023.

Category	**2017**		**2020**		**2023**	
	Freq.	**%**	**Freq.**	**%**	**Freq.**	**%**
Gender						
Male	1164	49.0	1019	50.1	2416	49.9
Female	1212	51.0	1017	49.9	2446	50.1
Age						
18-29	324	13.7	257	12.6	550	11.4
30-39	341	14.4	244	12.0	880	18.2
40-49	503	21.2	426	20.9	844	17.4
50-59	452	19.0	414	20.4	792	16.4
60-69	382	16.1	320	15.7	841	17.4
70+	374	15.8	375	18.4	736	15.2
Unknown	0	0.0	0	0.0	219	4.5
Geo. Area						
Centre	456	19.2	464	22.8	915	18.9
Islands	271	11.4	415	20.4	539	11.1
North Est	483	20.3	266	13.1	952	19.6
North West	637	26.8	479	23.5	1317	27.2
South	529	22.3	412	20.2	1139	23.5
Edu. Qual.						
High School	925	38.2	894	43.7	2535	52.3
Middle School	717	29.6	462	22.6	558	11.5
Univ. Level	537	22.2	331	16.2	973	20.1
No Education	1	0.0	44	2.2	21	0.4
Primary School	171	7.1	170	8.3	91	1.9
Other	47	2.0	27	1.3	57	1.2
Employ. Status						
Employed	867	36.5	769	37.6	2474	51.1
Retired	571	24.0	524	25.6	1172	24.2
Self-Employed	263	10.8	249	12.2	401	8.3
Student	161	6.8	121	5.9	291	6.0
Homemaker	264	11.1	247	12.1	349	7.2
Unemployed	229	9.6	126	6.2	142	2.9
Other	21	0.9	0	0.0	0	0.0
Refused	0	0.0	0	0.0	20	0.4
Unable to Work	0	0.0	0	0.0	13	0.3

Table 1: Data by Year and Category

Additionally, we standardized the subdimensions of financial knowledge, behavior, and attitudes assessed each year. In the following chapters, we elaborate on what each sub-index of every dimension evaluates. It's important to note that changes may have occurred across years, which we evaluated to arrive at a clear and standardized dataset.

3.2 Financial Literacy decomposed

For each year, we computed the subdimensions of financial literacy to gain a comprehensive understanding of its various facets. In the following paragraphs, we will explore the methods used to calculate these subdimensions. The overall level of financial literacy is given by the sum of these three components and it ranges between 1 and 21: a maximum of 7 points derives from the knowledge index, 9 from behaviour, and 5 from attitudes. Understanding these dimensions is crucial as they provide insights into specific areas of financial knowledge, behavior and attitude among different demographic groups over time.

3.2.1 Financial Knowledge

As previously mentioned, financial knowledge refers to an individual's understanding of basic financial concepts and their ability to apply numeracy skills in financial contexts. This knowledge is crucial for making informed decisions about financial products and services, allowing individuals to manage their financial matters autonomously and respond to financial news and events that may impact their well-being. Higher levels of financial knowledge are associated with positive outcomes such as increased stock market participation and better retirement planning, as well as reduced negative outcomes like debt accumulation. [OECD/INFE, 2016]

1. **FK1:** Purchasing Power
   - *Purpose:* To test the ability to understand how inflation impacts purchasing power.
2. **FK2:** Cost of a Loan
   - *Purpose:* To assess knowledge of the cost associated with borrowing money.
3. **FK3:** Simple Interest
   - *Purpose:* To evaluate understanding of basic interest calculation.
4. **FK4:** Understanding of Simple and Compound Interest
   - *Purpose:* To gauge comprehension of both simple and compound interest concepts.
5. **FK5:** Risk-Return Relationship
   - *Purpose:* To determine knowledge of the relationship between risk and potential return in investments.
6. **FK6:** Definition of Inflation
   - *Purpose:* To assess understanding of what inflation means economically.
7. **FK7:** Diversification of Risk
   - *Purpose:* To evaluate knowledge of the benefits of spreading investment risk across different assets.

Each sub-index of financial knowledge (FK1 to FK7) is assessed on a scale from 0 to 1 based on the responses to specific questions, indicating the level of comprehension of the concepts under evaluation. The total financial knowledge score is computed as the sum of these sub-index scores. By accurately answering these questions, individuals demonstrate a fundamental grasp of essential financial principles crucial for effective personal financial management in today's complex economic environment.

3.2.2 Financial Behaviour

Financial behavior encompasses the actions and decisions individuals undertake regarding their finances, reflecting their attitudes, habits, and choices in managing money. These behaviors are crucial as they directly impact financial well-being and stability. For this study, financial behavior was assessed through a series of questions designed to capture various aspects of financial management and decision-making.

1. **FB1:** Responsibility for Expenses and Budget
   - *Purpose:* To assess the level of responsibility in managing household finances.
2. **FB2:** Savings in the Last 12 Months
   - *Purpose:* To determine if the respondent has actively saved or invested money recently.
3. **FB3:** Careful Evaluation Before Purchases
   - *Purpose:* To evaluate whether the respondent carefully considers purchases before making them.
4. **FB4:** Timeliness in Bill Payments
   - *Purpose:* To assess punctuality in paying bills on time.
5. **FB5:** Control of Expenses
   - *Purpose:* To determine the degree of control over spending habits.
6. **FB6:** Long-Term Financial Goals
   - *Purpose:* To gauge the level of planning and commitment towards achieving long-term financial objectives.
7. **FB7:** Financial Instruments
   - *Purpose:* To understand the respondent's familiarity with and use of different financial products and services.
8. **FB8:** Negative Savings in the Last 12 Months
   - *Purpose:* To identify instances of financial setbacks or negative savings over the past year.

Each sub-index of financial behavior (FB1 to FB8) is scored differently: FB1 to FB6 and FB8 take values from 0 to 1, FB7 ranges from 0 to 2, and the total financial behavior score is the sum of these sub-index scores. Questions concerning sub-indices cover how survey participants handle their expenses, savings, bill payments, financial objectives, and their knowledge of financial tools. Understanding these dimensions provides insights into financial management practices and decision-making processes that are crucial for enhancing financial literacy and resilience across diverse demographic groups.

3.2.3 Financial Attitude

Financial attitude refers to an individual's perspective and predisposition towards financial matters, particularly concerning their preferences for short-term versus long-term financial planning and spending. This dimension is assessed using three key questions that gauge the respondents' agreement with statements about their financial attitudes. These statements focus on preferences for immediate gratification versus future security.

1. **FA1:** Tendency to Live for the Day
   - *Purpose:* To assess the respondent's attitude towards planning and preparing for the future.
2. **FA2:** Preference for Spending Over Long-Term Savings
   - *Purpose:* To understand the respondent's inclination towards immediate consumption versus saving for the future.
3. **FA3:** Money is Meant to be Spent
   - *Purpose:* To gauge the respondent's perspective on the purpose of money and financial resources.

Respondents use a 5-point scale to indicate their level of agreement, where 1 represents complete agreement and 5 represents complete disagreement. These questions aim to determine whether individuals prioritize short-term satisfaction over long-term financial stability. The scoring for financial attitudes is calculated by taking the average of the three responses, assuming equal relevance for each question. This method, despite some limitations in comparing scores across different datasets, provides a reliable approximation of individuals' financial attitudes. Understanding financial attitudes is crucial because it influences an individual's financial decision-making process, affecting their overall financial well-being.

Each subdimension contributes to the overall financial literacy score, providing a comprehensive view across demographic groups and over time. This decomposition helps understand the nuances in financial knowledge, behavior, and attitudes critical for enhancing financial literacy and resilience.

3.3 Demographic Segmentation by Age

A crucial step in the data preprocessing phase was dedicated to segmenting the population based on age. We decided to divide the data into three specific age groups to facilitate analysis and interpretation of the results. The defined categories are as follows:

- **Youngs**: up to 35 years. This category includes individuals who are in the early stages of their careers or still in education.
- **Adults**: from 35 to 59 years. This group encompasses individuals in their prime working and family-raising years.
- **Elders**: over 59 years. This category includes individuals who are generally approaching or are already in retirement.

To enhance the dataset, we added two new columns to the DataFrame. The first column, Age Label, indicates the age group label (Youngs, Adults, Elders) for each individual based on their age. The second column, Age Score, assigns a numerical score to each age group for further analysis, with Youngs assigned a score of 1, Adults a score of 2, and Elders a score of 3.

3.4 Structure of the final dataset

After the preprocessing phase, the final dataset is structured as shown in the following table. This standardized dataset includes common demographic variables, ensuring consistency across different survey years.

Variable name	**Description**
id	Individual identifier
anno	Wave's year
gender	Gender (0 Female, 1 Male)
geographical_area	Geographical area (1 North-West, 2 North-East, 3 Centre, 4 South, 5 Islands)
age	Age of peartecipant
age_label	Age category of the partecipant ("Giovani": up to 35 years, "Adulti": from 35 to 59 years, "Anziani": over 59 years)
age_score	Age score of the partecipant (1:Youngs, 2: Adults, 3: Elders)
edu_qualification	Educational qualification (1 University-level education, 3 Complete secondary school, 4 Some secondary school, 5 Complete primary school, 6 Some primary school, 7 No formal education)
employment_status	Employment status (1 Self-employed, 2 In paid employment, 4 Looking after the home, 5 Looking for work, 6 Retired, 9 Student, 10 Other)
FA1	FA1 score
FA2	FA2 score
FA3	FA3 score
FA	FA aggregate score
FK1	FK1 score
FK2	FK2 score
FK3	FK3 score
FK4	FK4 score
FK5	FK5 score
FK6	FK6 score
FK7	FK7 score
FK	FK aggregate score
FB1	FB1 score
FB2	FB2 score
FB3	FB3 score
FB4	FB4 score
FB5	FB5 score
FB6	FB6 score
FB7	FB7 score
FB8	FB8 score
FB	FB aggregate score
FL	FL score

Table 2: Structure of the final dataset

4 Exploratory Data Analysis (EDA)

4.1 Financial Literacy Overview

This section provides a comprehensive analysis of financial literacy across different socio-demographic variables based on data collected in Italy for the years 2017, 2020, and 2023. The discussion begins with gender-based differences in the Financial Literacy Index (FLI).

Figure 6 illustrates the average FLI scores for females and males across the three survey years. Females had average FLI scores of 11.11 in 2017, 10.84 in 2020, and 11.75 in 2023. In contrast, males scored 11.30 in 2017, 11.19 in 2020, and 12.32 in 2023. This data indicates that males consistently scored higher than females across all years, though both genders showed improvements in financial literacy from 2020 to 2023, with females demonstrating a significant increase compared to their 2020 scores (see Figure 6).

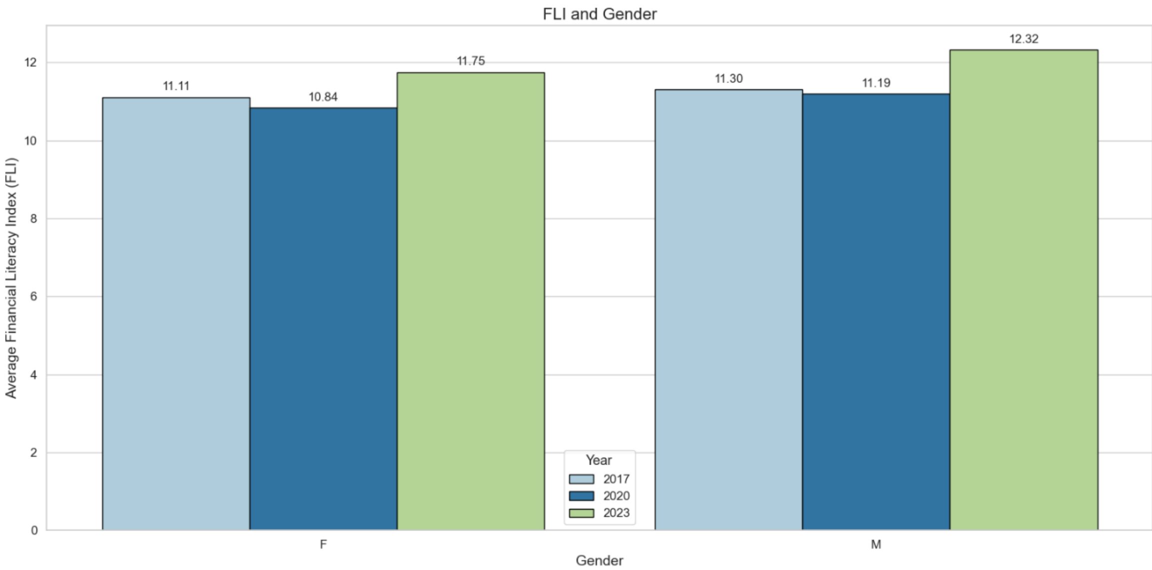


Figure 6: Average Financial Literacy Index (FLI) by Gender for the Years 2017, 2020, and 2023

The gender gap in financial literacy, while persistent, appears to be narrowing over time, particularly between 2020 and 2023.

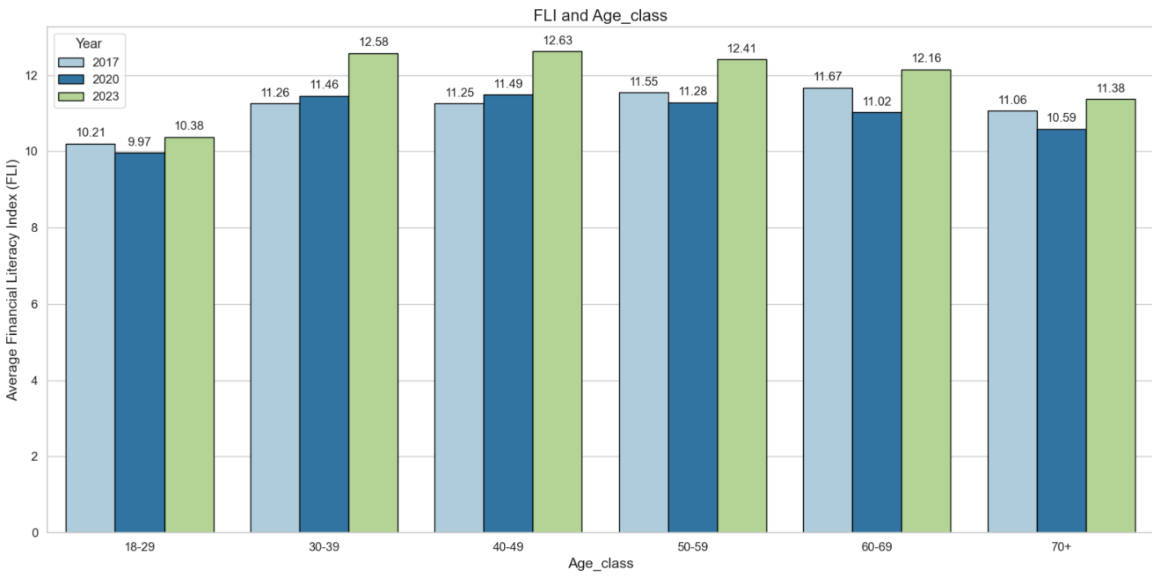


Figure 7: Average Financial Literacy Index (FLI) by Age Class for the Years 2017, 2020, and 2023

Figure 7 displays the average Financial Literacy Index (FLI) scores across different age classes. The data indicates differences in financial literacy among various age groups. Young adults, aged 18-29, showed lower average FLI scores in all three years: 10.21 in 2017, 9.97 in 2020, and 10.38 in 2023. This suggests a consistent challenge in financial education among younger demographics, highlighting the importance of targeted interventions to improve financial literacy early in adulthood. Conversely, the age groups 30-39, 40-49, 50-59, and 60-69 generally demonstrated higher FLI scores across the years surveyed. Notably, the 30-39 age group showed a notable increase from 11.26 in 2017 to 12.58 in 2023, indicating a positive trend in financial literacy among individuals approaching middle age. Similarly, the 50-59 age group also saw an improvement from 11.55 in 2017 to 12.41 in 2023, reflecting ongoing financial education efforts targeting this demographic. Among older adults aged 70 and above, FLI scores showed variability over the years, with a slight decrease from 11.06 in 2017 to 11.38 in 2023. This variability may reflect changing financial needs and capabilities as individuals transition into retirement and manage their financial resources differently.

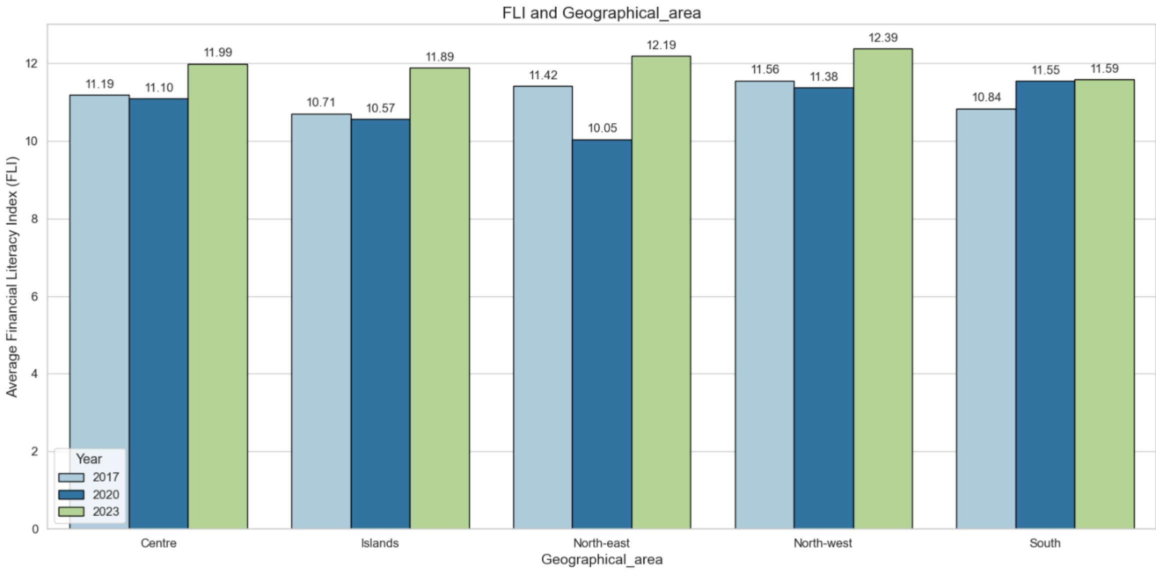


Figure 8: Average Financial Literacy Index (FLI) by Geographical Area for the Years 2017, 2020, and 2023

Then, Figure 8 illustrates the average Financial Literacy Index (FLI) scores across different geographical areas in Italy for the years 2017, 2020, and 2023. The data reveals notable variations in financial literacy across different regions of Italy. In 2017, respondents from the North-west region showed the highest average FLI score at 11.56, while those from the Islands had the lowest at 10.71. By 2023, however, the North-west region had surpassed other regions with an average FLI score of 12.39, indicating significant improvement in financial literacy. Conversely, the Islands region also showed notable improvement, increasing from 10.57 in 2020 to 11.89 in 2023. The Centre region consistently demonstrated moderate FLI scores across the years, with slight fluctuations from 11.19 in 2017 to 11.99 in 2023. Similarly, the South region showed variability in FLI scores, increasing from 10.84 in 2017 to 11.55 in 2020, then stabilizing at 11.59 in 2023. Notably, the North-east region exhibited a decline in FLI scores from 11.42 in 2017 to 10.05 in 2020, followed by a recovery to 12.19 in 2023. This variability suggests regional differences in financial literacy levels influenced by economic conditions, educational programs, and cultural factors.

Figure 9 depicts the average Financial Literacy Index (FLI) scores across different education levels in Italy for the years 2017, 2020, and 2023. The data shows clear differences in financial literacy depending on level of education. Individuals with higher levels of education consistently exhibit higher FLI scores across all three years surveyed. In 2017, respondents with a university-level education or higher had the highest average FLI score at 12.04, followed by those with a high school diploma at 11.50. Similarly, in 2020 and 2023, these groups maintained higher FLI scores compared to individuals with lower educational attainment levels. Respondents with a middle school diploma showed moderate FLI scores across the years, with slight fluctuations from 10.52 in 2017 to 10.86 in 2023. Individuals with only a primary school diploma consistently showed lower FLI scores, decreasing from 10.28 in 2017 to 9.82 in 2023. The disparity in FLI scores between educational groups widened over time. In 2023, individuals with a university-level education or higher had an average FLI score of 13.09, while those with a primary school diploma scored 9.82.

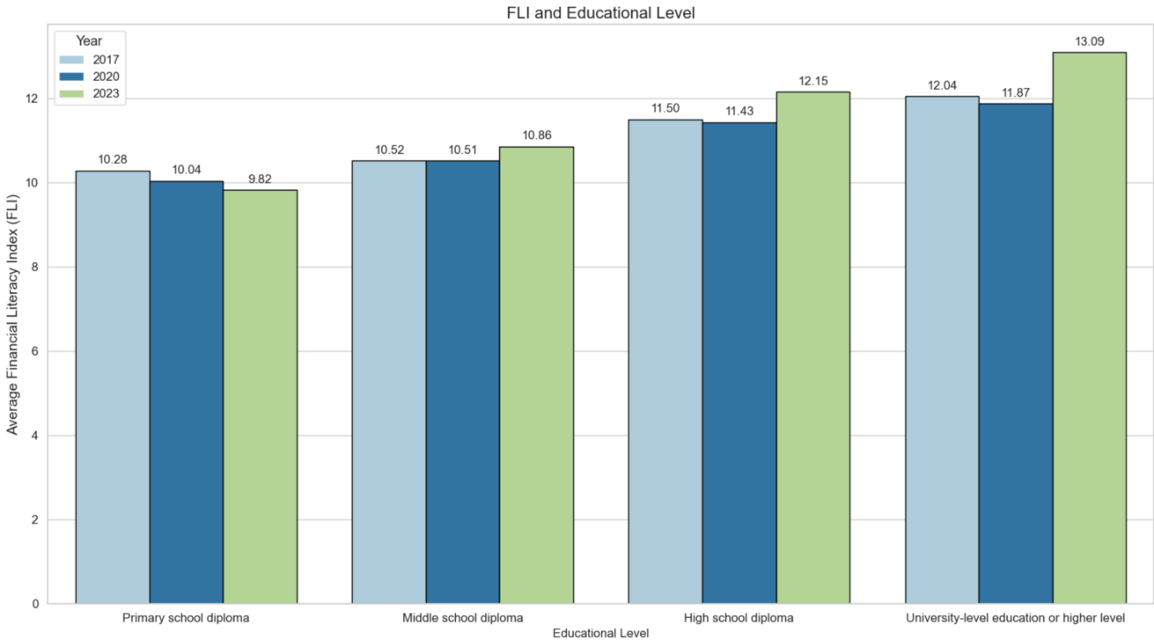


Figure 9: Average Financial Literacy Index (FLI) by Education Level for the Years 2017, 2020, and 2023

Finally, Figure 10 displays the average Financial Literacy Index (FLI) scores across different employment statuses in Italy for the years 2017, 2020, and 2023. The data vividly demonstrates the stark contrasts in financial literacy across different employment groups. In 2017, employed individuals exhibited the highest average FLI score at 11.60, followed closely by self-employed individuals at 11.55. Retired individuals also showed strong FLI scores at 11.44. Conversely, students and unemployed individuals had lower FLI scores at 10.08 and 10.35, respectively. By 2020, there were shifts in FLI scores among different employment groups. Self-employed individuals experienced a significant increase in FLI scores to 12.36, surpassing employed individuals whose FLI score slightly decreased to 11.30. Retired individuals experienced a decline in FLI scores to 10.75, while students and unemployed individuals also showed decreases in FLI scores. In 2023, the trends continued with notable changes in FLI scores across employment statuses. Employed individuals showed an increase in FLI scores to 12.65, indicating improved financial literacy. Self-employed individuals maintained high FLI scores at 12.91, reflecting their continued focus on financial management. Retired individuals also demonstrated an increase in FLI scores to 11.86. However, students and unemployed individuals showed the lowest FLI scores at 9.52 and 9.58, respectively, highlighting ongoing challenges in financial literacy among these groups.

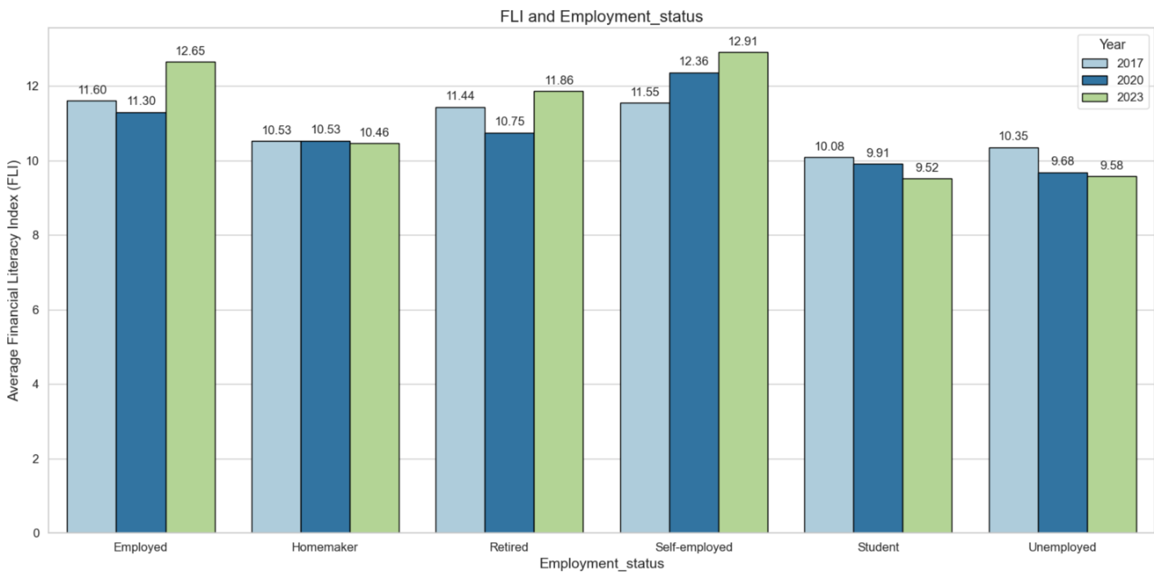


Figure 10: Average Financial Literacy Index (FLI) by Employment Status for the Years 2017, 2020, and 2023

These findings underscore the multifaceted nature of financial literacy across different demographic groups in Italy. Effective strategies to enhance financial education should address specific socio-demographic needs and challenges, promoting inclusive economic growth and resilience.

5 Self-Organizing Maps on Aggregated Financial Literacy Subdimensions

Self-Organizing Maps (SOMs), conceptualized by Professor Kohonen (1982), represent a valuable tool within the domain of unsupervised artificial neural networks. SOMs are trained through a competitive learning framework, consisting of two fundamental units: the input layer and the output layer. The output layer is organized as a two-dimensional lattice of codebooks, which stand for neurons that map input data based on distance measures. In this framework, a specific neuron "wins" in better representing a particular input unit compared to other codebooks. The weights of the winning neuron and its neighbors are iteratively updated to improve map accuracy.

The efficacy of SOM models in preserving proximity between raw observations and achieving robust results with ordinal-scale data has been demonstrated by various studies [Adamczyk et al., 2013, Silva et al., 2023]. For instance, Arcagni et al. [2019] employed SOMs to explore social fragility and poverty among migrants in Northern Italy. Their study demonstrated the utility of SOMs in visualizing the distribution of ordinal-scale coded patterns, revealing structural differences in poverty levels across ethnic groups. Additionally, SOMs facilitate clustering analyses by grouping codebooks with similar attribute values, as highlighted by Yigit [2023].

In accordance with these insights, we developed SOMs using both unsupervised and supervised approaches to analyze aggregated financial literacy subdimensions, specifically financial attitude (FA), financial behavior (FB), and financial knowledge (FK). These attributes were derived from each single attribute of aggregated subdimension following OECD decoding instructions. The analysis was guided by the following questions:

1. Is it possible to identify groups within the data across the three financial literacy dimensions without considering external attributes?
2. Do variations in value distributions emerge within each financial literacy dimension?
3. Can socio-demographic variables elucidate more complex patterns, revealing potential cluster differences among groups?

'Kohonen' R package Wehrens and Kruisselbrink [2023] was used for analyzes performing, whereas *'aweSOM'* R package Boelaert et al. [2022] was implemented for computing model R-squared and quantization error measures.

5.1 Unsupervised analyzes

Starting from an agnostic approach, disposition of the three subdimensions composing the overall financial literacy according to the sample values has been observed, without any external variable guiding the SOM training. A grid of 5 * 5 size has been chosen, in order to avoid the construction of empty codebooks (further trials have been employed: improvements of grid size of a single dimension unit leads to nodes without units linking). APPENDIX A, Table 3 reports hyperparameter values. From plots in Figure 11, the following suggestions arise:

- Despite the presence of node regions which represent row units adeuqately (darker depicted in 11.a), lighter colors in half of the codebooks reveal higher distances from data representation. Nevertheless, the quantization error, which has been computed as the average squared distance between the data points and the map's prototypes, is around 0.44, demonstrating that the node lattice is efficient in representing ground truth.
- On the other hand, the presence of a wide colored-homogeneous region of dark-red nodes in U-matrix (11.b) suggests the presence of small distances between nodes. However, R-squared value of around 0.85 indicates that SOM is able to explain data variance.
- By observing values distributions among codebooks (11.d), a heterogeneous picture is addressed since nodes with higher values in all the three subdimensions, mostly grouped in the left-lower part of the plot, are heavily counterbalanced with codebooks having at least one null-like subdimension in value, leading to hypothesize the presence of remarkable differences among sample subjects.

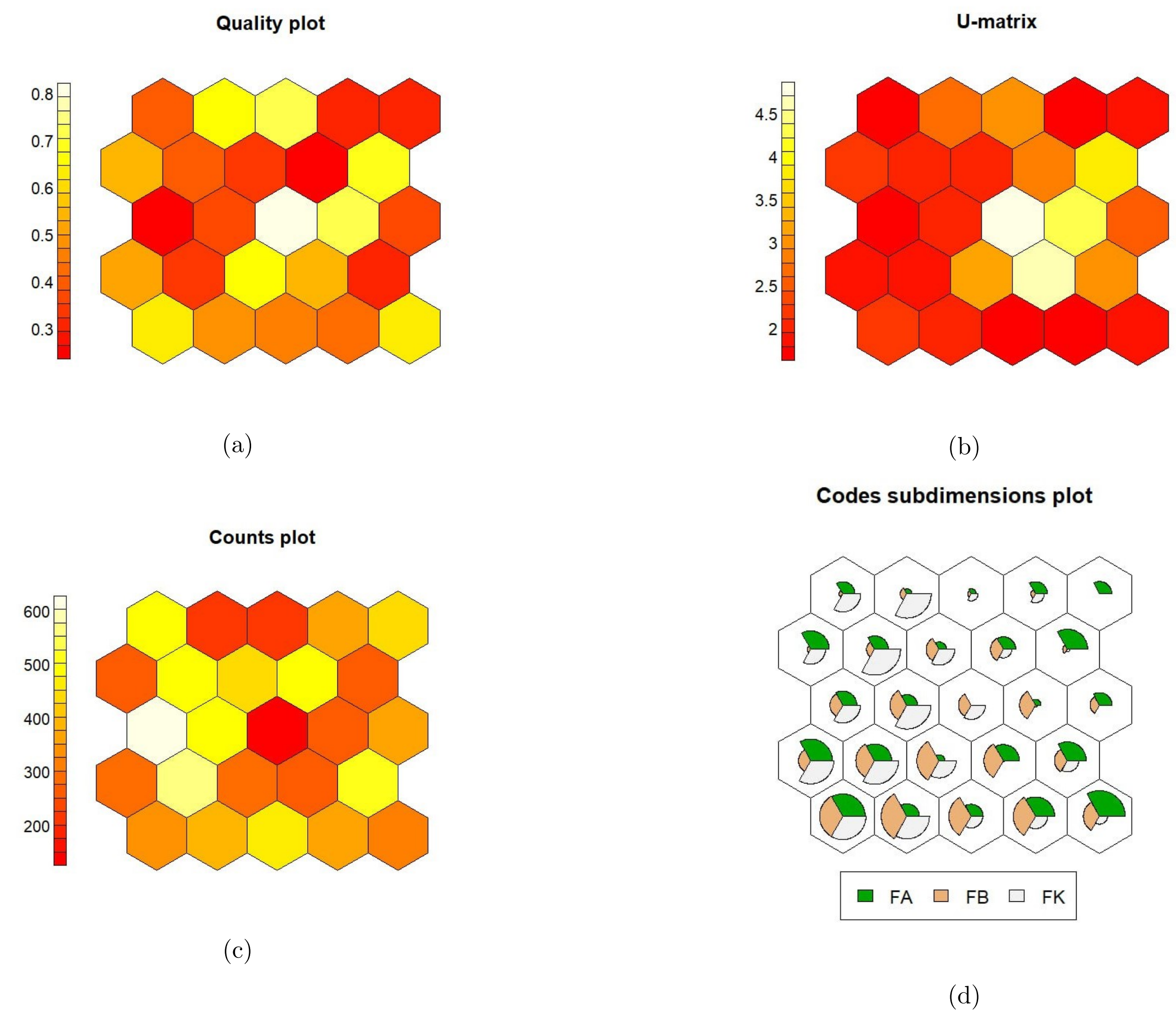


Figure 11: a) quality plot shows the mean distance of the units represented by a specific codebook vector, to its belonging node. The lower the distance, the better the node representation; b) U-matrix shows the sum of the distances of each node to its neighbours; c) Counts plot shows, for each node, how many units are represented by it; d) Codebook vectors plot shows, for each node, average component value sizes

5.1.1 Component plans

In order to explore how dimension values were distributed across observations, the following steps have been addressed:

- First, an expansion of the map through a two-stage iterative process has been encompassed, with the purpose of better visualize graphical results in higher definition maps (APPENDIX A, Table 4 reports the entire explanation on how expansion layers have been built)
- Second, a graphical function for distance smoothness to create homogeneous regions of nodes has been applied.

Figure 12 shows that upon analyzing the components, it becomes evident that there it might be observed a disproportionate distribution of the FA, FB, and FK scores. Specifically, the graphical resolution allows us to observe the density degree of map regions with high values of the subdimensions compared to those with lowers. From a strictly qualitative point of view, the graphs seem to suggest that, in the case of financial attitude, greater values are revealed (lighter lattice areas) compared to those with lower scores (darker areas) with respect to the trend observed in financial behavior. The distribution of financial knowledge shown an intermediate situation where the scores are equally distributed between high and low scores nodes.

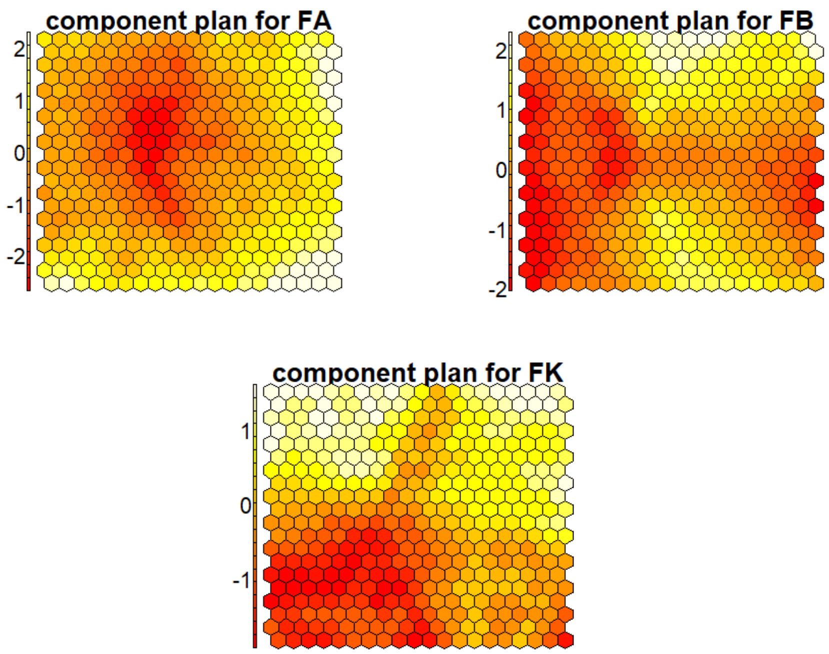


Figure 12: The figures display on a color scale the arrangement of normalized values for the subdimensions FA, FB, FK. Dark colors of the nodes correspond to low values, while light colors refer to higher values.

5.1.2 Clustering analysis

By developing the final suggestion of the previous paragraph, a clusterization of the nodes has been employed (APPENDIX A for clustering process details). Best clustering representation is reached through 3 codebook groups (Silhouette coefficient is around 0.35), drawn using different hues in Figure 13.

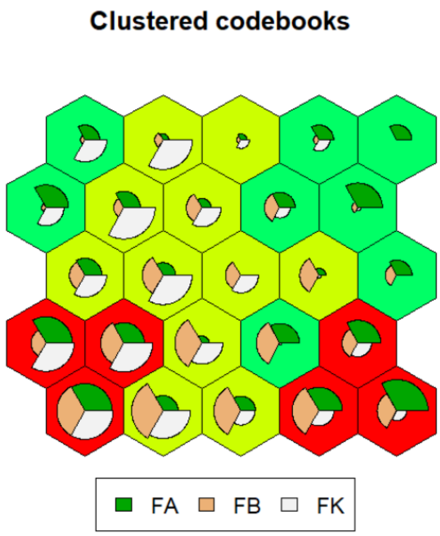


Figure 13: Unsupervised clustered codebook vectors plot. Three different hues identify the same number of different groups: red, yellow and green respectively.

Specifically, the plot highlights interesting hints:

- Imbalance in clusters size is addressed: red-colored nodes are shortly lower in amount with respect to those displayed in green, whereas are much lower than yellow ones which are the largest in numbers.

- Remarkable differences in values between centroid codebook vectors emerge: red group, which is linked to row data getting higher values in all the three subdimensions, shows on average maximum FA scores (normalized value= 1.02) and low scores in FB (-0.26) and FK (-0.36). Yellow nodes, which represent the widest in size cluster, show high value in FA (0.72), medium-level scores in FK (almost zero, which is related in quite perfect average value if considering denormalized value) and the lowest level of FB (-0.57). The green cluster instead, is related to a general low scores trend across the three subdimensions (FA=0.38, FB=-0.23, FK=-0.55). Despite the differences in score values, financial attitude shows the highest value in all of the three groups.

To summarize, this initial analysis demonstrates that observations exhibiting high values across all three subdimensions of financial literacy are numerically fewer compared to those with intermediate or even lower values. Subsequent analyses will aim to provide additional insights into the factors contributing to a more informative segmentation of the population, particularly in terms of the distribution of values across the subdimensions of financial literacy.

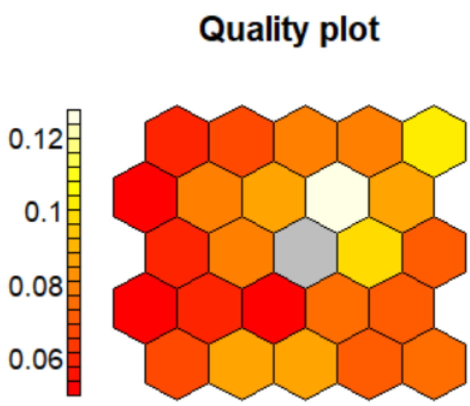
5.2 Supervised univariate analyzes

In order to try to give an answer to the third question mentioned at the beginning of this section, supervised analyzes were conduct since the possibility of differences among FL subdimensions scores in considering socio-demographic variable could be revealed. We chose to perform such that analyzes over different age classes and geographical areas, following an univariate approach (the two categorial attribute were considered separately). Choice of reducing analyzes to two attributes was made since they were the only ones whose recording have been made in all of the three recordings years, without any codification changes across survey versions. Furthermore, we do not consider other possible variables since a risk of not-interestingness in findings could arise (for example, one can expect that, in considering employment status, substantial differences between people who are unemployee and those employed should be detected, reaching an obvious-like conclusion).

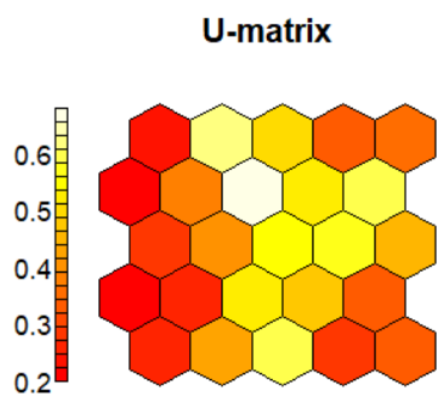
5.2.1 Age class

Age categories as described in 3.3 were taken into account, using "age_label" column. SOM was trained in this case using *xyf* function by kohonen R package. Again, a grid size of 5*5 was chosen, which has been observed to be an efficient tradeoff between larger size (with the risk of obtaining null codes), and smaller ones. APPENDIX B, Table 6 reports specifications towards hyperparameter values which were employed. By observing plots shown in Figure 14, the following can be carried out:

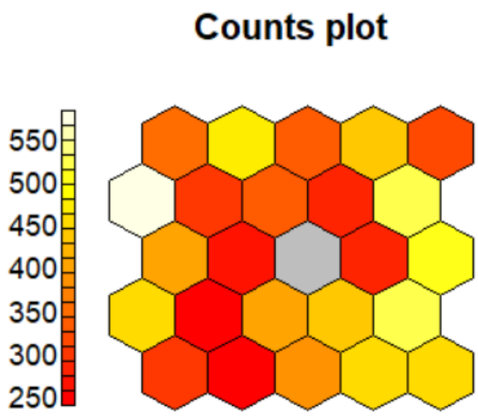
- The nodes lattice seems to represent row data in a more efficient way than in the unsupervised approached, as quality plot displays a large amount of codebooks in darker hues, thus revealing minimum distances from real data. Quantization error is estimated to be around 0.89, corroborating these suggestions since it is lower than 1.
- U-matrix shows greater distances between codebooks, with a fewer number of them grouping together in a more homogeneous-in-distance region (dark red)



(a)



(b)



(c)

Figure 14: a) Quality plot showing mean distances between each node and its representing; b) U-matrix showing the sum of the distances of each node and its neighbours; c) Counts plot showing how many units are represented by each node

Codes plots in Figure 15 anticipate that an effect of age class in guiding nodes segmentation may have been obtained, since all the 25 codebooks (with except of the 13th node) show the relevance in amount of one single age class. In the next subsection results of the clustering analysis will be discussed in order to go more in depth with this topic.

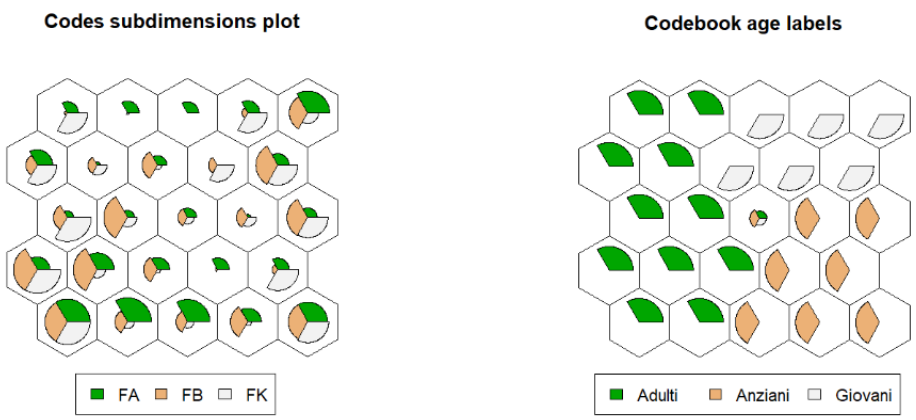


Figure 15: Left plot shows codebook vectors referring to the average component value sizes for each node; right plot shows vectors clustering driven by the external variable

5.2.1.1 Clustering

Clustering analysis was performed according to the specifications described in APPENDIX B. Figure 16 displays the 3 groups of nodes (Silhouette coefficient is around 0.5), driven from the external variable. R-squared index is equal to 0.70, demonstrating high performance in explaining variance in ground truth from the constructed model.

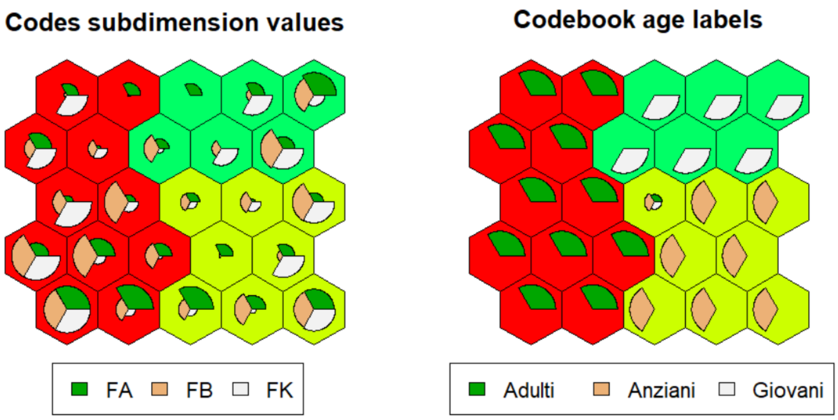


Figure 16: Supervised clustered codebook vectors plot. Three different hues identify the same number of different groups: red, yellow and green respectively. Left plot refers to vectors clustering; right plot shows the impact of the external variable in driving clustering

Despite the class imbalance, since adults nodes are significantly more in number, remarkable differences between clusters are detected:

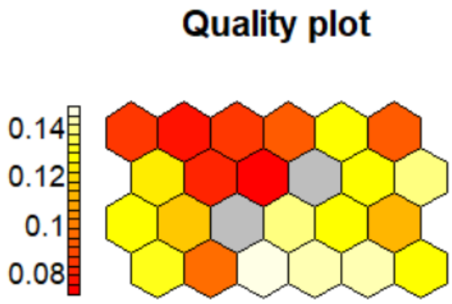
- adults, show average values of FA and FB which are positive in sign (APPENDIX B, Table 7 for a tabular report): normalized score are equal to 0.12 and 0.32 respectively. On the other hand, significantly lower results are addressed in FK (-0.21).
- elderly people seem to show an intermediate trend: FA is the subdimension with the highest average score (0.06), whereas FB and FK show a more deficient picture with scores of -0.33 and -0.06.
- young people are represented by six nodes and show interesting differences from the other groups: specifically, they seem to exhibit an opposite trend to that shown by adults. While they got the worst FA score (-0.61) and a still low average level of FB, they achieved the highest average normalized values in FK (0.53).

The analysis suggests a heterogeneous picture where adults lead to observe a stronger financial attitude, while younger individuals seem to get higher levels of financial knowledge compared to other age groups. Notably, none of the three clusters show high average values of financial behavior, indicating that the implementation of virtuous behaviors in financial literacy remains a significant challenge.

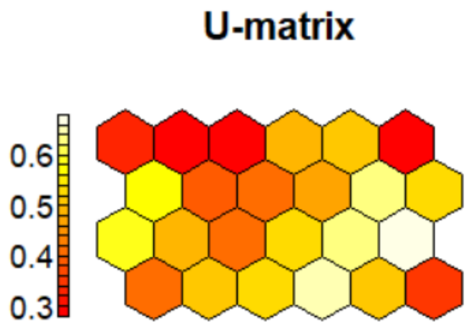
5.2.2 Geographical area

"Geographical_area" column has been used as external variable. SOM training has been performed using *xyf*. After multiple trials in tuning grid size, a 6*4 lattice was chosen, which led to smaller training error (APPENDIX C, Figure 24). Plots in Figure 17 suggest that:

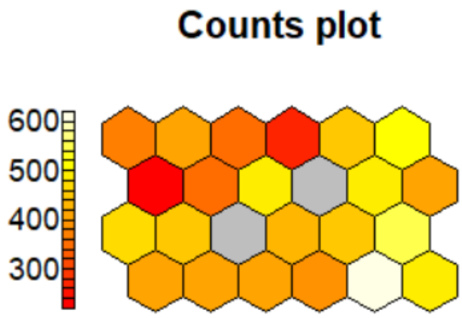
- Contrary to what was observed for age class as an external variable in the supervised learning of the SOM, a greater distance from the codebooks and their respective units emerges. From the quality plot, we can detect a reduced region of dark red nodes, associated with low values of the distance measure, compared to those colored in lighter shades (high distance values with the raw data). Additionally, a quantization error of about 1.31 leads to suggest that a general lack of representativeness of the map was got;
- on the other hand, the U-matrix shows that the codebooks are adequately separated, although there remains a minimal region of neighboring nodes.



(a)



(b)



(c)

Figure 17: a) Quality plot showing mean distances between each node and its representing; b) U-matrix showing the sum of the distances of each node and its neighbours; c) Counts plot showing how many units are represented by each node

Figure 18 qualitatively shows the effect of supervised learning considering the geographic area as an external variable. It can be seen that most of the nodes seem to cluster around the North-west regions, while a more homogeneous distribution emerges for the other geographic areas. The subsequent clustering analysis will help to better understand if any differences between groups can be identified.

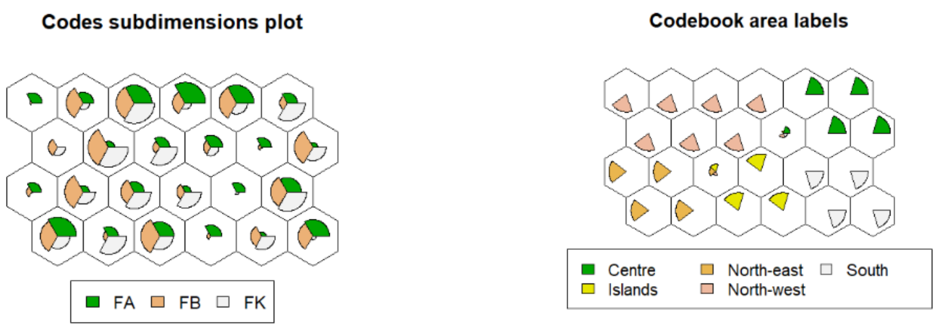


Figure 18: Left plot shows codebook vectors referring to the average component value sizes for each node; right plot shows vectors clustering driven by the external variable

5.2.2.1 Clustering

Silhouette best coefficient, as well as graphical observation of the dendrogram (APPENDIX C Figure 25a) guided a 5-clusters segmentation, guided by a Silhouette coefficient of 0.30. The R-squared shows that the model explains 56.26% of the variance in the data, a significantly lower value compared to the previous scenario.

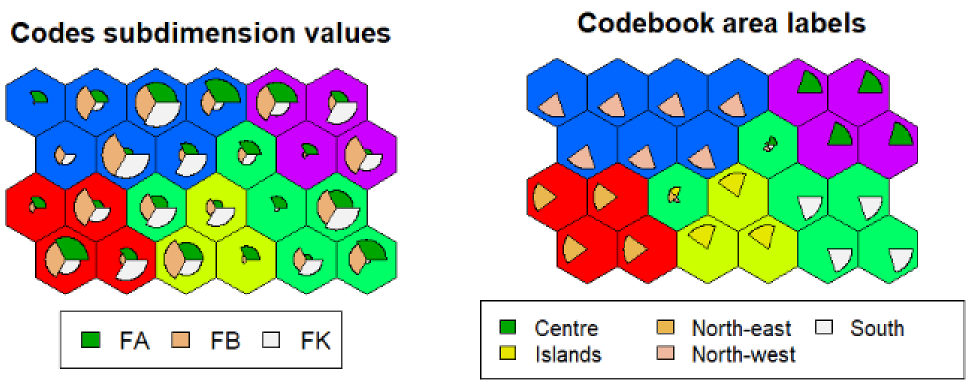


Figure 19: Supervised clustered codebook vectors plot. Five different hues identify the same number of different groups: red, yellow, green, purple and blue respectively. Left plot refers to vectors clustering; right plot shows the impact of the external variable in driving clustering

From Figure 19, the following observations can be made:

- once again, the external variable appears to have effectively guided the clustering process. The five different geographical areas cluster into five distinct groups (Silhouette coefficient is around 0.50, APPENDIX C, Fig. 25a).
- analyzing the normalized mean values of the cluster centroids (APPENDIX C, Table 9), it can be noticed that Cluster 2 (yellow), which corresponds to the insular regions, registers the highest FA scores (0.56). On the other hand, this same geographical area shows the worst FB result (-0.67).
- cluster 3 (green), representing the southern regions, exhibits results which is opposite to that seen for the previous geographical area: it is associated with the highest FB levels (0.42) but at the same time reveals the lowest FA scores (-0.52).
- clusters 1 and 4 (red and purple, respectively representing the northeast and northwest regions) fall into an intermediate range of scores, while Cluster 5 (blue) related to central Italy, despite decent FK values (0.39), registers significantly low FB values (-0.56).

6 Conclusion and future development

This study provides a comprehensive examination of financial literacy (FL) in Italy over the years 2017, 2020, and 2023, highlighting significant disparities and trends. Italy's economic landscape has undergone significant changes in recent years, influencing the financial behaviors and literacy of its citizens. Key economic indicators such as Gross Domestic Product growth, consumer prices, and household disposable income have been observed undergoing through a challenging time-window, with a severe risk of vulnerability.

Findings in our explorative data analysis analysis indicate persistent gender disparities in financial literacy, with males consistently outperforming females, though the gap appears to be narrowing over time. FL scores across different educational attainment also emerge, with higher education levels linking with better financial literacy scores. In considering the employment status, self-employed and employed individuals let to observe higher financial literacy scores compared to students and unemployed individuals

The application of Self-Organizing Maps (SOMs) to analyze financial literacy attributes revealed that the overall levels of financial literacy in Italy appear to be modest. Among the various dimensions of FL, financial behavior is identified as the most deficient. This indicates that many individuals may lack the practical skills and habits necessary for effective financial management, such as budgeting, saving, and prudent spending.

Significant sociodemographic differences are evident. Notably, young people represent the most at-risk demographic group, exhibiting the poorest performance in financial attitudes. This result is even more negative when considering that FA is one of the more preserved subdimensions of FL in Italy. This highlights a critical gap that needs to be addressed to lead better financial attitudes and behaviors among the youngs.

Geographic differences are evident too, with Southern and Insular regions showing significant negative peaks in at least one of the FL subdimensions. Regional disparities underline the necessity for targeted interventions to enhance financial literacy in areas with weaker FL scores, ensuring more equitable access to financial education and resources.

Investing in financial literacy is crucial since one in three people worlwide is not adequately financially literate [Klapper and Lusardi, 2020]. This global perspective underscores the widespread nature of the issue and the need for comprehensive financial education initiatives.

Financial literacy is a protective factor against the risks of financial distress [Bialowolski et al., 2022, Klapper and Lusardi, 2020, Bialowolski et al., 2022]. Specifically, Bialowolski et al. [2022] demonstrated that the impact of financial literacy on financial resilience becomes smaller with age, emphasizing the importance of early financial education.

Our analyses emphasized the need for early financial education interventions. Research by [Koh et al., 2010] indicates that this generation, despite their higher education levels and technological skills, often exhibits indecision in financial matters due to protective upbringings. Additionally, many young people are burdened with high credit loads and lack an understanding of saving for retirement. Surveys by the American Savings Educational Council and AARP [2008] and studies by VP et al. [2008] highlight similar trends in other countries, noting new financial challenges such as access to credit, rising education and healthcare costs, and inflation.

In conclusion, addressing the identified gaps in financial literacy through targeted educational initiatives and policies is needed. Such efforts may promote better financial practices, reduce regional and sociodemographic disparities, and boost a more financially literate and resilient population in Italy. The insights taken from this research provide a valuable foundation politics and educators to develop and implement strategies that will improve financially literate and economically stable society in Italy.

For more details, you can view the full project on GitHub: https://github.com/Full-Project.

Appendix A

SOM Hyperparameters	Value
Grid size	5 * 5
Training iterations	200
Learning rate	0.05, 0.01

Table 3: SOM Hyperparameters

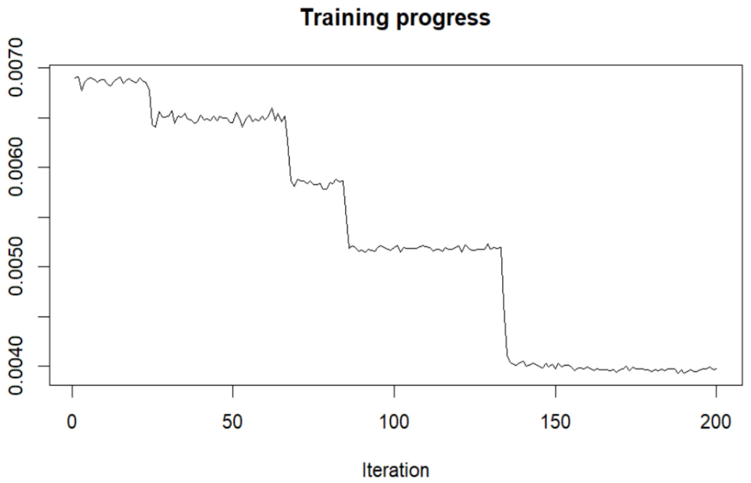


Figure 20: The plot shows the learning process of the unsupervised SOM, by computing the units mean distance to the closest node

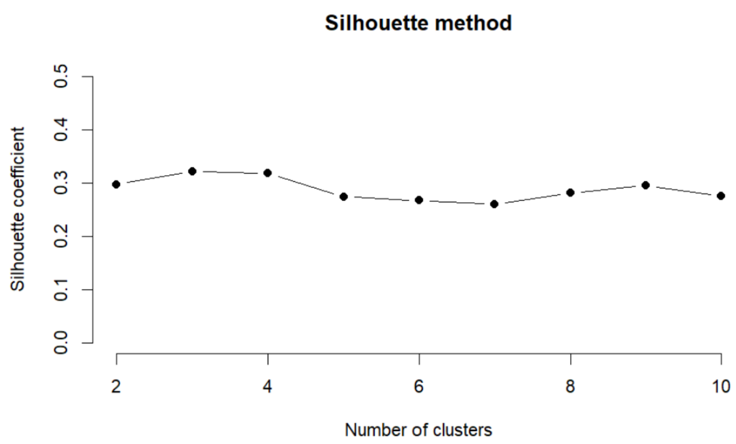
Component Plans Hyperparameters	Value
Grid expanded (layer 1)	10 * 10
Training iterations (layer 1)	100
Learning rate (layer 1)	0.05, 0.01
Grid expanded (layer 2)	20 * 20
Training iterations (layer 2)	100
Learning rate (layer 2)	0.05, 0.01

Table 4: Component Plans Hyperparameters

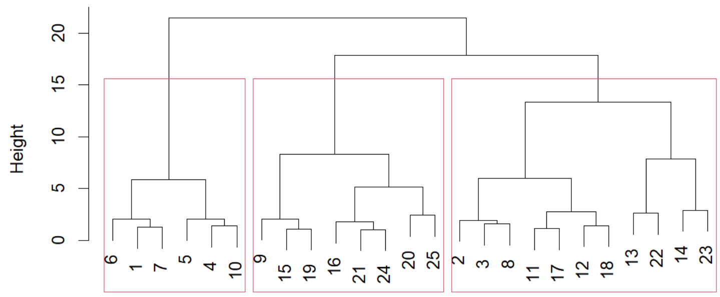
Clustering

Clusterization has been employed according to the following pipeline:

1. First, codebook distances were extracted from Kohonen object post-defined SOM function.
2. Hierarchical clustering over distances is then computed.
3. In order to assess clustering performance in different dendrogram cutting values, an iterative process where Silhouette coefficients computation among a range of 2-10 clusterizations was performed.
4. Finally, the lower in k-size but higher in silhouette coefficient number of clusters was chosen (k = 3), as suggested also by the dendrogram in Figure 21 (b).



(a)



(b)

Figure 21: a) Silhouette coefficient vs. number of clusters, indicating clustering quality from 2 to 10. A value equal to three is supposed to be the best tradeoff as links to the higher coefficient; b) Hierarchical clustering dendrogram

	Centroid Vector Values		
	FA	**FB**	**FK**
Cluster 1	1.02	0.72	0.38
Cluster 2	-0.26	-0.03	-0.23
Cluster 3	-0.36	-0.57	-0.55

Table 5: The computation of the centroid vector values involved the following steps: (1) extracting the codebook vectors, (2) grouping them by clusters, and (3) computing the mean values for each cluster. The resulting matrix contains these average values. See Rmd script for code

Appendix B

SOM Hyperparameters	Value
Grid size	5 * 5
Training iterations	200
Learning rate	0.05, 0.01

Table 6: SOM Hyperparameters

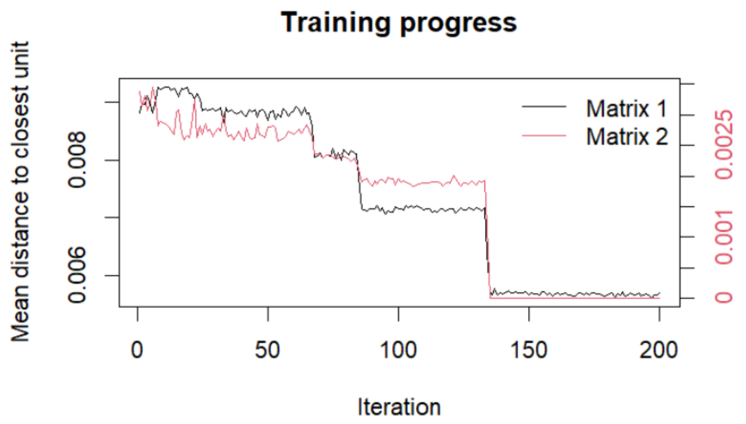
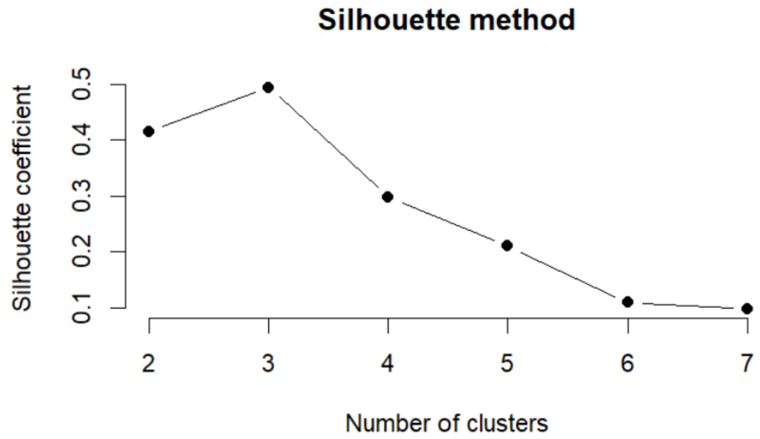


Figure 22: The plot shows the learning process of the supervised SOM, by computing the units mean distance to the closest node. Matrix 1 curve refers to learning iteration process of subdimension vectors, whereas Matrix 2 curve refers to learning process of vectors driven by the external variable

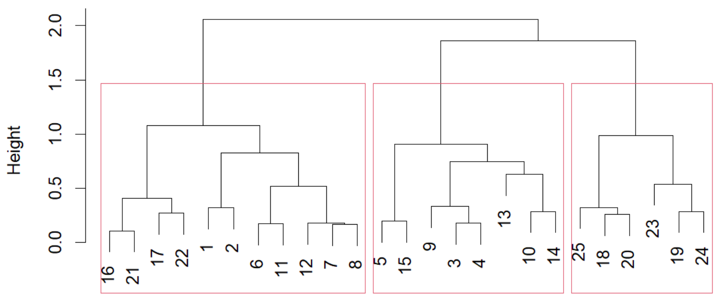
Clustering

Clusterization has been employed according to the following pipeline:

1. First, codebook distances were extracted from kohonen object post-defined som function, using xyf which accept values matrix and target variable as parameters.
2. Hierarchical clustering over distances was then computed
3. In order to assess clustering performance in different dendrogram cutting value, an iterative process where Silhouette coefficients computation among a range of 2-7 clusterization was performed.
4. Finally, the lower in k-size but higher in silhouette coefficient number of clusters was chosen (k = 3), as suggested also by dendrogram in Figure 23 (b)



(a)



(b)

Figure 23: a) Silhouette coefficient vs. number of clusters, indicating clustering quality from 2 to 7. A value equal to three is supposed to be the best tradeoff as links to the higher coefficient; b) Hierarchical clustering dendrogram

	Centroid Vector Values		
	FA	**FB**	**FK**
Cluster 1	0.12	0.32	-0.21
Cluster 2	0.06	-0.33	-0.06
Cluster 3	-0.69	-0.37	0.53

Table 7: The computation of the centroid vector values involved the following steps: (1) extracting the codebook vectors, (2) grouping them by clusters, and (3) computing the mean values for each cluster. The resulting matrix contains these average values. See Rmd script for code

Appendix C

SOM Hyperparameters	Value
Grid size	6 * 4
Training iterations	350
Learning rate	0.05, 0.01

Table 8: SOM Hyperparameters

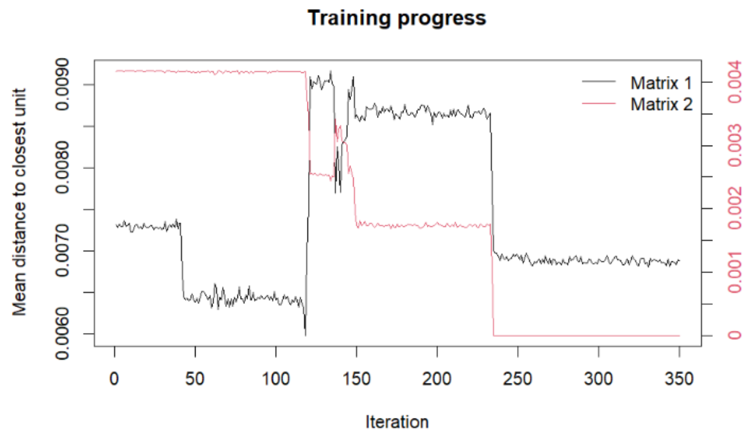
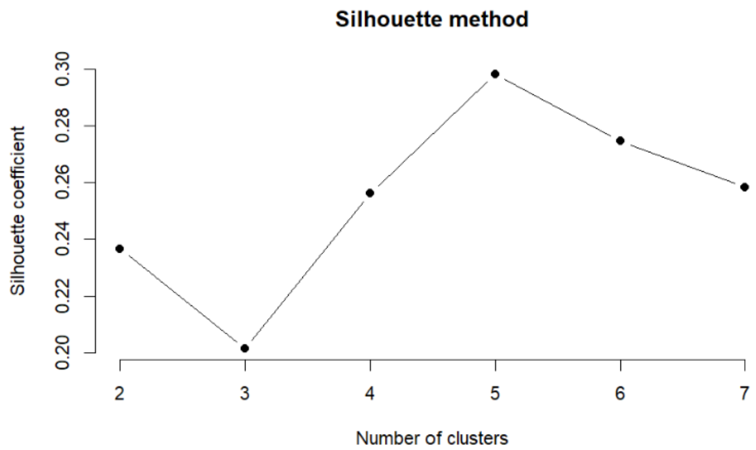


Figure 24: The plot shows the learning process of the supervised SOM, by computing the units mean distance to the closest node. Matrix 1 curve refers to learning iteration process of subdimension vectors, whereas Matrix 2 curve refers to learning process of vectors driven by the external variable. It is noticeable that the learning process for the external variable appears to be challenging: specifically, the learning curve worsens between the 120th and 230th iterations before improving again

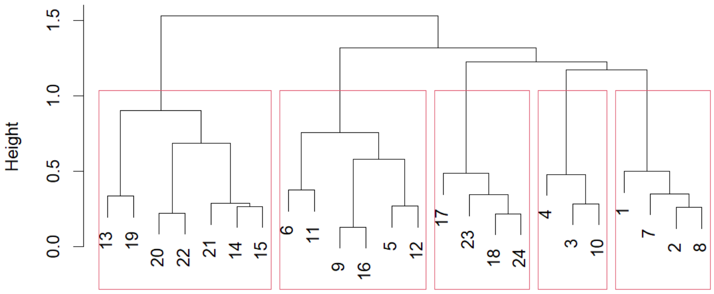
Clustering

Clusterization has been employed according to the following pipeline:

1. First, codebook distances were extracted from kohonen object post-defined som function, using xyf.
2. Hierarchical clustering over distances was then computed
3. In order to assess clustering performance in different dendrogram cutting value, an iterative process where Silhouette coefficients computation among a range of 2-7 clusterization was performed.
4. Finally, the lower in k-size but higher in silhouette coefficient number of clusters was chosen (k = 5), as suggested also by dendrogram in Figure 25 (b).



(a)



(b)

Figure 25: a) Silhouette coefficient vs. number of clusters, indicating clustering quality from 2 to 7. A value equal to five is supposed to be the best tradeoff as links to the higher coefficient; b) Hierarchical clustering dendrogram

	Centroid Vector Values		
	FA	**FB**	**FK**
Cluster 1	0.16	0.07	-0.16
Cluster 2	0.57	-0.67	-0.18
Cluster 3	-0.52	0.43	0.04
Cluster 4	0.07	-0.02	0.10
Cluster 5	0.17	-0.56	0.39

Table 9: The computation of the centroid vector values involved the following steps: (1) extracting the codebook vectors, (2) grouping them by clusters, and (3) computing the mean values for each cluster. The resulting matrix contains these average values. See Rmd script for code

Appendix D

Questionnaire questions

The following questions are based on the 2017 questionnaire.

D.1 Financial Knowledge

The responses to seven questions are used to compare levels of financial knowledge.

1. First question: Time-value of money (QK3) Assume that you receive a gift of €1.000. Imagine that you have to wait for one year to get it and inflation stays at 1%. In one year's time will you be able to buy:

Answer	**Value assigned**
a) More than you could buy today	1
b) The same amount	2
c) Less than you could buy today	3
d) Don't know	-97
e) No answer	-99

2. Second question: Interest paid on a loan (QK4) You lend €25 to a friend one evening and he gives you €25 back the next day. How much interest has he paid on this loan?

Answer	**Value assigned**
a) answer	
b) Don't know	-97
c) No answer	-99

3. Third question: Interest plus principal (QK5) Suppose you put €100 into a tax free savings account with a guaranteed interest rate of 2 percent per year. You don't make any further payments into this account and you don't withdraw any money. How much would be in the account at the end of the first year, once the interest payment is made?

Answer	**Value assigned**
a) answer	
b) Don't know	-97
c) No answer	-99

4. Fourth question: Compound interest (QK6) And how much would be in the account at the end of five years [remembering there are no fees or tax deductions and you don't make any further payments into this account and you don't withdraw any money]?

Answer	**Value assigned**
a) More than €110	1
b) €110	2
c) Less than €110	3
d) It is impossible to tell from the information given	4
e) Don't know	-97
f) No answer	-99

Questions 5,6 and 7. Risk and return, Definition of inflation and Diversification (QK7_1 to QK7_3) I would like to know whether you think the following statements are true or false:
1=True, 0=False, -97=Don't know, -99= No answer

Statement	**Response**
a) An investment with a high return is likely to be high risk.	answer
b) High inflation means that the cost of living is increasing rapidly	answer
c) It is possible to reduce risk of investing in a stock market by buying a wide range of stocks.	answer

D.2 Financial Behaviour

1. First question: Responsible and has a household budget (QF1) Who is responsible for making day-to-day decisions about money in your household? (single answer)

Answer	Value assigned
a) You make these decisions by yourself	1
b) You make these decisions with other household members	2
c) Other household members (not you)	3
e) No answer	-99

2. Second question: Responsible and has a household budget (QF2) A household budget is used to plan what share of your household income will be used for spending or saving. Does your household have a budget to plan in advance which share of income will be used for spending and which share will be saved for the next years?

Answer	Value assigned
a) Yes	1
b) No	0
c) No answer	-99

3. Third question: Active saving (QF3_1, QF3_3, QF3_4, QF3_6, QF3_6, QF3_8, QF3_99) In the past 12 months have you been personally saving money in any of the following ways, whether or not you still have the money? Please do not include pension savings (multiple choice)

Question	Answer	Value of QF3
a) Saving cash at home or in your wallet	☐	_1
b) Paying money into a savings account	☐	_3
c) Giving money to family to save on your behalf	☐	_4
d) In some other way (remittances,buying livestock,gold or property)	☐	_6
e) No	☐	_7
f) Has not been actively saving	☐	_8
g) No answer	☐	_99

4. Fourth question: Considered purchase, timely bill payment, keeping watch of financial affairs and Long term financial goal setting (QF10_1, QF10_4, QF10_6, QF10_7) I am now going to read out some statements. I would like to know how much you agree or disagree that each of the statements applies to you, personally. Please use a scale of 1 to 5, where 1 tells me that you completely agree that the statement describes you, while 5 shows that you completely disagree (1=Totally agrees, 5=Totally disagrees, -97=Don't know, -99=No answer)

Question	Answer	Value of QF10
a) Before I buy something I carefully consider whether I can afford it	☐	_1
b) I pay my bills on time	☐	_4
c) I keep a close personal watch on my financial affairs	☐	_6
d) I set long term financial goals and strive to achieve them	☐	_7

5. Fifth question: Choosing products (Qprod2 and Qprod3)

Qprod2: Which of the following statements best describes how you made your choice? (single answer)

Answer	Value assigned
a) I considered several options from different companies before making my decision	1
b) I considered the various options from one company	2
c) I didn't consider any other options at all	3
d) I looked around but there were no other options to consider	4
e) No answer	-99

Qprod3: Which sources of information do you feel most influenced your decision? (multiple choice)

Answer	Value of Qprod3
a) Unsolicited information sent through the post	_1
b) Information picked up in a branch	_2
c) Product specific information found on the internet	_3
d) Information from sales staff of the firm providing the products	_4
e) Best-buy tables in financial pages of newspapers/magazines	_5
f) Best-buy information found on the internet	_6
g) Specialist magazines/publications	_7
h) Recommendation from independent financial adviser or broker	_8
i) Advice of friends/relatives (not working in the financial services industry)	_9
j) Advice of friends/relatives (who work in the financial services industry)	_10
k) Employer's advice	_11
l) Newspaper articles	_12
m) Television or radio programs	_13
n) Newspaper adverts	_14
o) Television adverts	_15
p) Other advertising	_16
q) My own previous experience	_17
r) Other source	_18
s) No answer	_19

6. Sixth question: Borrowing to make ends meet (QF12)
What did you do to make ends meet the last time this happened? (multiple choice)

Answer	Value of QF_12
a) Draw money out of savings	_1_a
b) Cut back on spending, spend less, do without	_1_b
c) Sell something that you own	_1_c
d) Work overtime, earn extra money	_1_d
e) Borrow from family or friends	_1_e
f) Borrow from employer/salary advance	_1_f
g) Pawn something that you own	_1_g
h) Use authorized, arranged overdraft or line of credit	_1_k
i) Use credit card for a cash advance or to pay bills/buy food	_1_l
j) Take out a personal loan from a financial service provider	_1_m
k) Take out a loan from an informal provider/moneylender	_1_o
l) Use unauthorized overdraft	_1_p
m) Pay my bills late; miss payments	_1_q
n) Other	_1_r
o) Don't know	_1_97
p) No answer	_1_99

D.3 Financial Attitude

4. Attitude question: (QF10_2, QF10_3, QF10_8) I am now going to read out some statements. I would like to know how much you agree or disagree that each of the statements applies to you, personally. Please use a scale of 1 to 5, where 1 tells me that you completely agree that the statement describes you, while 5 shows that you completely disagree (1=Totally agrees, 5=Totally disagrees, -97=Don't know, -99=No answer)

Question	Answer	Value of QF10
a) I tend to live for today and let tomorrow take care of itself	☐	_2
b) I find it more satisfying to spend money than to save it for the long term	☐	_3
c) Money is there to be spent	☐	_8

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