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Research article

Relationship between an inconsistent degree of financial literacy and inconsistent decision-making in intertemporal choices

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ABSTRACT

Intertemporal choice refers to the decision-making process involving trade-offs between rewards available at different points in time (such as choosing between smaller immediate rewards versus larger rewards later on). Empirical evidence often deviates from the exponential preferences predicted by the normative model. A hyperbolic discount function better mirrors individual behavior, explaining temporal inconsistency – whereby preferences vary over time by applying a higher discount in the present. Hyperbolic preferences are associated with addictive behaviors, such as smoking and alcohol consumption, as well as depression or attention deficit hyperactivity disorder. Established measures in the literature quantify the extent of deviation from exponential trend exhibited by hyperbolic preferences.

In addition to behavioral and cognitive factors, it is essential to incorporate financial literacy into the examination of individual decision-making behaviors. The present study analyzes the relationship between the degree of decision-making inconsistency and the degree of financial literacy inconsistency across three dimensions: knowledge, behavior, and attitudes. It aims to illustrate while financial literacy is important, it is not sufficient to ensure rational choices. Rather, it reveals a strong correlation among its dimensions. The results of this research could be included when creating investor profiles required by MiFID, considering insights from behavioral finance studies in these profiles. What is more, understanding psychological biases that can influence financial decision-making empowers investors to make more informed decisions and avoid common pitfalls.

1. Introduction

Intertemporal choice involves the consideration of exchanges (such as costs, benefits, or welfare) across time. The costs and benefits associated with a choice are distributed over time. Decisions regarding actions like adhering to a healthy diet or exercising more involve immediate costs but yield long-term benefits, like improved health, increased life span. The same occurs with decisions related to saving for retirement. Commonly, a discount function is implicit in the intertemporal choice process. Theoretically, individuals employ the discounted utility model, which implies an exponential discount function with a constant discount rate. However,

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empirical evidence suggests that this assumption is not always correct, revealing variability in the discount rate, leading to temporal inconsistency (i.e., [1]). Said variability can explain problematic behaviors related to self-control and long-term orientation of individuals, manifesting as varying degrees of impatience. Long-term orientation significantly impacts individual well-being, in terms of both physical and financial health.

Conversely, it has been suggested that possessing financial literacy (FL) positively influences the financial decisions that individuals make throughout their lives, e.g., reducing excessive credit usage and increasing savings rates. Therefore, offering financial education is beneficial for citizens. In Spain, for example, the CNMV (The Spanish Securities and Exchange Commission) and the Bank of Spain launched a four-year Financial Education Plan in 2008 [2], which has already been renewed three times. Financial education benefits individuals at all stages of life, regardless of their income level. Being financially literate helps individuals make better financial decisions, such as initiating early retirement savings or adhering to credit card limits. The policy implications of these findings are that the implementation and improvement of financial education programs can significantly enhance citizen well-being [3].

According to Ref. [4], there is a positive association between less impatient individuals and higher financial knowledge, indicating a greater likelihood for this group to spend time acquiring financial literacy or information.

In [5], it was found that financial education can be an effective method in reducing temporary discounting, implying that it could aid in decreasing impatience levels. They assessed financial education by means of a semester-long course. In addition, similar results were obtained by Refs. [6,7] by means of shorter programs explaining key financial concepts like compound interest, the time value of money, and capitalization risk.

The reduction of impatience levels not only contributes to making better financial decisions but also extends to other fields, such as health. High discount rates (indicative of high impatience) have also been linked to unhealthy eating habits and addictive behaviors (e.g. [8–11]). In this line [12], found that patients with a history of substance abuse who received personalized instruction on adhering to budget planning and monitoring experienced a decrease in delay discounting, as well as a reduction in cocaine use.

Although evidence supports the impact of financial literacy on the ability to make rational choices [13], further exploration is necessary to develop interventions aimed at improving hyperbolic discounting tendencies. Indeed, individual decision-making is the result of psychobiological and behavioral factors that necessitate thorough analysis of their interdependence. Moreover, financial literacy alone appears insufficient to comprehensively understand decision-making behaviors [14].

In this regard, it is crucial to acknowledge that financial literacy comprises a set of components that combine to determine its overall level. These components encompass: Financial Knowledge (FK), which refers to understanding main concepts; Financial Behavior (FB), related to the behavioral and decision-making aspects; and Financial Attitude (FA), concerning underlying attitudes and beliefs.

These components are interconnected and mutually influential: strong financial knowledge can positively influence behavior, leading to more informed and responsible choices. However, it is not always the case that those with a high level of FK present a high level of FB, as the decision-making process is determined by the interaction of multiple factors, such as age, gender, and background. This potential inconsistency among FK, FB and FA highlights that promoting financial literacy necessitates promoting all contributing components.

To investigate the relationship between psychobiological factors and the characteristics of sound financial literacy, the present study proposes an analysis to determine the relationship between decision-making inconsistencies in intertemporal choices and inconsistencies among the components of financial literacy. Since inconsistencies in intertemporal choices involve the phenomenon whereby individuals may alter their original preference if a significant delay in choice options is introduced [15], the aim is to understand how decision inconsistency aligns with the interactions among the three components of financial literacy. Indeed, given that attitudes in intertemporal choices are linked to psychobiological characteristics and that the impact of financial literacy on decision-making remains a subject of discussion in the context of behavioral finance [16,17], the present study aims to enrich the understanding of the relationship among FK, FB, and FA with respect to the consistency of individual choices.

Furthermore, with respect to the stated objectives, the originality of this survey addresses two aspects – methodological and structural. The methodology used employs the combination of decision-making techniques based on hierarchical decomposition and aggregation of weights. This approach is indispensable and innovative, seeking to decompose the three components of financial literacy related to individual characteristics. It investigates how they interact when aggregated to form a single score and how this relates to the effectiveness of the decision-making process. The uniqueness of the structure lies in the consideration of the three components of financial literacy as individual elements. This method defines a projection of the decision-maker across multiple levels, enriching the description of the relationship under investigation.

The analysis involves a combination of the AHP (Analytic Hierarchical Process), Markov chains and OWA (Ordered Weighted Averaging) aggregation operators. The AHP facilitates the decomposition of FL into its main components, classified into 4 clusters through the K-means algorithm. The Markov chains justify the transition from component weights to probabilities of transiting among different FL dimensions. OWAs are employed to aggregate the transition probabilities across all possible combinations while preserving the relative importance of the different information. The scores obtained will be correlated with the degree of inconsistency of the discount function, as measured in Refs. [18,19].

The proposed analysis confirms a correlation between higher degrees of decision inconsistency in intertemporal choices and a higher degree of inconsistency among FL components. Furthermore, decomposition obtained using the AHP, also discussed with respect to gender, highlights the importance of tailored interventions to encourage positive financial behavior and to promote healthy financial attitudes across all FL components.

The present study is structured as follows: the second section explains the method and analysis measures in detail, the third section discusses the results collected, followed by a discussion section and a conclusion that delve into the main findings, research limitations, possible practical applications, and suggestions for future studies.

2. Methods and scope

The analysis aims to explore the relationships between the degree of coherence among the dimensions constituting financial literacy [20,21] and the degree of inconsistency of the discount function. Specifically, financial literacy (FL) is comprised of financial knowledge (FK), financial behavior (FB), and financial attitude (FA). FK measures the understanding of basic financial concepts; FB evaluates attitudes related to proper financial resource management, such as monitoring expenditure, savings and payment habits. Lastly, FA assesses attitudes towards expenditure planning and savings practices. The alignment among the three scores is referred to as the congruence of the triad (FK, FB, FA). For example, an individual with high FK and low FB and FA may display potentially low coherence. Examining this coherence in relation to the inconsistency of the discount function makes it possible to investigate how the combination of the three indices leads to consistent choices over time.

The proposed individual questionnaire consists of two parts: the first measures FK, FB, FA, and consequently FL using an adapted version of [20] to our sample. The second constructs the individual discount function [18,19].

The questionnaire was implemented via an online platform, designed and written by a Software Developer (acknowledged in the paper) according to the authors' specifications. The questionnaires used and submission instructions can be found in the cited sources. Employing an online platform enabled increased user participation without prolonging the duration of the study and ensured a more diverse sample. The authors shared the link on various social platforms and disseminated it in both academic and non-academic circles.

After questionnaire completion, data obtained from the online platform were converted into a csv file using a Python algorithm, extracting user profile data including gender, the degree of the three FL components, and values of the discount function at different time points.

The data analysis, on the other hand, involved several techniques. Initially, individual projection with respect to the three FL components was conducted.-. Subsequently, an aggregation of this decomposition was carried out in relation to the degree of decision inconsistency in intertemporal choices.

Data analysis is therefore based on a combination of four tools: the k-means algorithm, the Analytic Hierarchical Process [22], Markov chains [23] and Ordered Weighted Averaging (OWA) [24].

The k-means algorithm is an unsupervised clustering method that divides a dataset into K groups based on their similarities. AHP is a useful decision support method for complex problems involving the evaluation of multiple alternatives against multiple, non-directly comparable criteria. In practice, AHP establishes a hierarchical structure that deconstructs the decision problem into levels, providing a structured method for obtaining a weighted evaluation of the final level with respect to all previous levels. In fact, the process is based on analyzing relationships between elements of one level with respect to the elements of the next level.

A Markov chain is a type of stochastic process, evolving randomly over time, characterized by transitions and states. Each state is assigned a probability of transition to one or more subsequent states, expressed by the transition matrix. The Markov property states that transition probabilities depend solely on the current state.

OWAs are aggregation operators that combine a set of weighted values in a non-linear fashion. OWAs consider the relative importance of input values, sort them, and apply weights to define the output. This aggregation aligns well with the objectives of the present study, as it allows for both value averages and their dispersion to be considered.

Data collection, constructing the AHP, interpreting the weights obtained in terms of transition probabilities, and aggregating all possible combinations of the triad (FK, FB, FA) constitute the main steps in analyzing FL coherence. Even though AHP and Markov chains lack a direct relationship, they can be used in a supplementary way to obtain a more accurate description of the decision problem and more precise and effective modelling [25,26].

In the present study, the combination of AHP and Markov chains allows the relative priorities of FK, FB, and FA to be interpreted as the initial state of the individual and as a transition vector from one state to all others. In this sense, the degree of inconsistency in the triad (FK, FB, FA) is defined by aggregating the correspondence of the transition probabilities across all possible state combinations.

The AHP structure is comprised of five levels, with the first representing the overall objective of the process: *assessing coherence within FL*. The subsequent levels include FL, FK, FB, and FA, each of which encompasses four classes: '1′ very low, '2′ low, '3′ medium and '4′ high. The nomenclature has been chosen to emphasize the average score of the sample (10.94) and the presence of negative scores on a scale of 1–24 points.

In terms of the general aim, the second level includes FL to project the weight of the four FL classes in relation to the sample's measure consistency. The subsequent levels are ordered according to the significance of the FL dimensions. Since FL and FK are closely related, as FK is an essential component of FL, the third level is composed of the four classes of FK. In turn, FK and FB are linked because financial knowledge can influence an individual's behavior. For instance, people who know more about financial products are more likely to make better choices. However, the relationship between FK and FB is not linear and should not be taken for granted. Indeed, more knowledge does not necessarily lead to more responsible action; emotions and personal beliefs are important factors. This is precisely why the FB level is followed by the FA level, which is an expression of an individual's beliefs, emotions, and values concerning money and financial management.

2.1. Inconsistency in intertemporal choice

The reference model for describing intertemporal preferences is the Discounted Utility Model [27,28]. Intertemporal utility combines the perception of the outcome utility with the discount function evaluated at the moment when the decision maker will actually receive the good. Thus, the role of the discount function is to reduce present utility according to the decision maker's perception of future uncertainty. The psychological mechanisms underlying the reduction of present utility over time are encapsulated in the discount factor, which represents the proportional change in the discount function across a standard period [29]. Impatience, conversely, expresses how much one is willing to sacrifice in order to receive a unit of money immediately [30].

In line with a rational decision-maker model, the discount function is typically defined with an exponential trend, necessary to preserve decision consistency over time. This assumption is equivalent to requiring a constant discount factor and degree of impatience across time [31]. However, empirical evidence has revealed discrepancies between the expected and observed behaviors in individuals, motivating the search for and definition of hyperbolic discount functions that align more closely with real intertemporal preferences [32]. Hyperbolic models are characterized by a sharper discount in the present, i.e., a discount factor and a degree of impatience that decrease over time.

The degree to which impatience decreases over time has been discussed in relation to non-rational preferences [31] and emotional impulses and cognitive factors [16] involved when evaluating a prospectus. With respect to the discrepancy between the hyperbolic and exponential model, several studies have also discussed the relationship between decision-making and subjective time perception [18,19,33]. Time, in fact, is crucial in intertemporal choices, not only because the choice depends on how one perceives the indeterminacy of the future but also on how the future itself is perceived as more or less distant.

Hyperbolic discounting has been used as a tool for studying mechanisms, such as obesity [34], attention deficit hyperactivity disorder [35], schizophrenia [36] and addiction [37]. The Delay Discounting (DD) task [10,38–41] is the most widely used application for quantifying discounting. This task involves individuals choosing between immediate and minor (SS) or delayed and major (LL) outcomes, that is "smaller sooner" versus "larger later" rewards.

Non-rationality is captured by the preference inversion mechanism, whereby a decision maker alters SS and LL choices over time and discount functions are presented with different descriptive and statistical measures [42] which facilitates the scoring procedure for estimating the discount rate [43,44].

The present work uses the approach formalized by Refs. [18,19,45] to delineate a more precise construction of the discount function using the interpolation technique. This greater precision is also related to the fact that individuals need not choose between options established by the experimental design but rather define indifference pairs over time. This step enables the capture of even the smallest differences in individual preferences, thereby enhancing the descriptive power of the hyperbolic discount model. In this work, inconsistency is measured as the maximum distance between the interpolated hyperbolic function and its optimal exponential interpolation. Thus, for each individual, the discount function is constructed as defined by Ref. [18]):

$$\mathrm{f}(\mathrm{t}) = \begin{cases} \mathrm{f}(0) = 1 \\ \mathrm{f}(\mathrm{t}_{\mathrm{i}+1}) = \dfrac{\mathrm{f}(\mathrm{t}_{\mathrm{i}}) * \mathrm{U}(\mathrm{x}(\mathrm{t}_{\mathrm{i}}))}{\mathrm{U}(\mathrm{x}(\mathrm{t}_{\mathrm{i}+1}))} \end{cases}$$

The values of the discount function to be interpolated are obtained by the following question:

"You have to receive $\mathrm{U}(\mathrm{x}(\mathrm{t}_{\mathrm{i}}))$ euros today, how much do you want to receive in $\mathrm{t}_{\mathrm{i}+1}$ days to consider the offer equivalent?"

fixed $U_D(x(0)) = 100€,\ t_0 = 0$ and $t = 0, 2, 4, 7, 10, 14, 20, 30, 45, 60, 90$.

3. Analysis

3.1. General analysis

The experiment was conducted through an online questionnaire. The final sample consisted of 206 individuals, with an average age of 27.64.Among them, 57.77% were women, averaging 27.12 years, while 42.23% were men, averaging 28.38 years.

The first step is the clustering of FL, FK, FB, and FA. By implementing the k-means algorithm in Matlab, 16 classes were obtained, as shown in Table 1.

The extrapolation of the weights in Fig. 1 was obtained following [17], while the relative weights for each level are shown in Table 2.

Starting with the first level, it is possible to observe how the sample is distributed about a minimum FL of 13.67, specifically within cluster 4. Nevertheless, it should not be assumed that the sample is suitably prepared in terms of FL. The sum of clusters 2 and 3 indicates that most of the sample, 58.73%, scored between 1.17 and 13.42 on a 24-point scale, highlighting a tendency towards a low

Table 1
Clustering of FL, FK, FB, and FA.

Clustering code	1	2	3	4
Variable	Very Low	Low	Medium	High
FL	**(-7.65, -2.06)**	**(1.17, 7.79)**	**(8.05, 13.42)**	**(13.67, 23.33)**
FK	(-6.79, 0.16)	(1.04, 4.10)	(5.00, 7.03)	(8.00, 9.00)
FB	(-6.87, −0.88)	(0.03, 4.04)	(5.00, 7.02)	(8.00, 10.00)
FA	(-0.97, 1.67)	(2.00, 3.33)	(3.67, 4.33)	(4.66, 5.00)

Source: Own elaboration. The columns represent the intervals against which the sample scores are grouped.

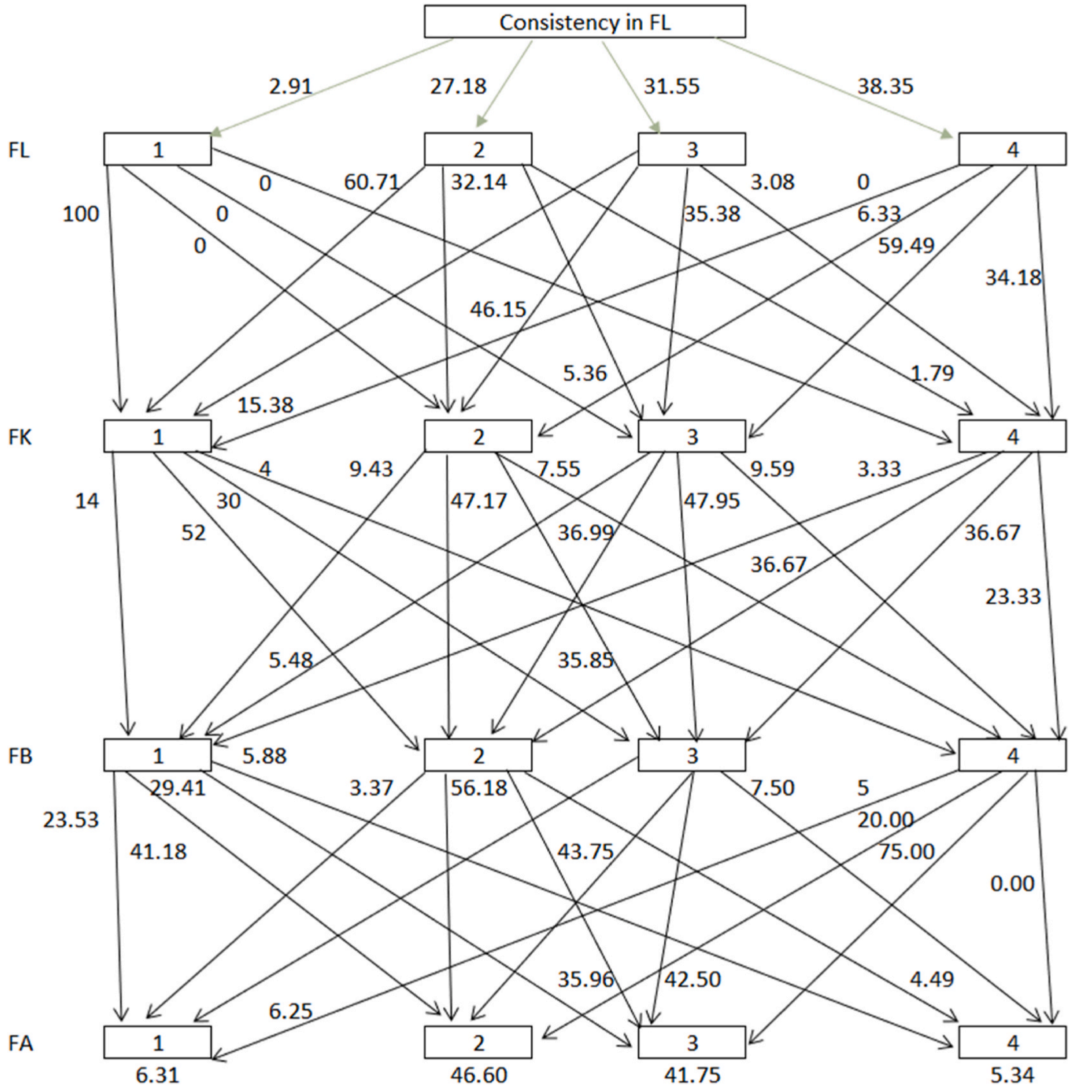


Fig. 1. Final AHP. Source: Own elaboration.

Table 2
Relative weights for each level of the AHP shown in Fig. 1 and Global Weight of the last level. The weights were obtained as in Ref. [17].

Clustering Code	Relative Weight FL	Relative Weight FK	Relative Weight FB	Global Weight FA
1	2.91	24.27	8.25	6.31
2	27.18	25.73	43.20	46.60
3	31.55	35.44	38.83	41.75
4	38.35	14.56	9.71	5.34

The weight of an individual's beliefs, emotions, and values about money and financial management corresponds to financial behavior.
Source: Own elaboration.

to medium FL level. In addition, approximately 3% of individuals have a negative FL score.

The strong correlation between FK and FL is clear from the analysis of the second level. FL1 has zero-weight compared to FK2, FK3, and FK4, aligning entirely with FK1 and implying that a very low degree of FK directly corresponds to a very low degree of FL. The link between FK and FL is also evident in grades 2 and 3: individuals with a very low degree of FK have a low-medium degree of FL, while those with medium-high FK have high FL. It is also important to note the null correspondence between FL4 and FK1, which confirms the importance of financial knowledge with respect to financial understanding and management.

The relationship between FK and FB, on the other hand, is less direct, but still evident from the correspondences FK2-FB2 and FK3-FB3. Notably, non-zero correspondences are observed between FK1-FB4 and FK4-FB1: possessing a high level of financial knowledge does not signify the ability to behave rationally, and correct behavior is not always linked to financial knowledge. This result emphasizes that the individual subjective dimensions must be related and overlapped to understand how FL level is consistent, which underlines the importance of the present research. Indeed, the hierarchical decomposition highlights inconsistent correspondences that surpass the idea of correlation among dimensions.

Of particular interest is the association FB1-FA4, indicating that behavior can display low quality despite positive attitudes, highlighting a lack of management skills and self-control. On the other hand, FB4-FA1 indicates that awareness of one's beliefs and understanding one's emotions and values can lead to medium to high-quality behavior despite lacking positive attitudes. The process ends with a logical representation of a medium to low-quality sample. Cluster 4 also exhibits the lowest weight.

3.2. Differentiated analysis male-female

To investigate gender-based behavioral differences in relation to previous observations, the sample was divided into male (M) and female (F) groups, resulting in two AHPs, shown in Figs. 2 and 3, and summarized in Table 3. With respect to the first level, the difference between FL1_F and FL1_M is immediately apparent: the former is approximately four times larger than the latter. Although, in general, women show a lower degree of FK, mainly occupying the FK1 and FK2 classes, as detailed in Table 3.

Continuing to the FB level, the comparison of AHPs shows a pronounced incongruence between FK1 and FB4: men demonstrate roughly three times the weight compared to women. This suggests that, in general, men tend to exhibit superior financial behavior, regardless of their knowledge. However, for women only, both the relationship between FK4 and FB1 and between FB4 and FA1 are null. This could indicate a greater correspondence between knowledge, behavior, and attitudes among women. Furthermore, there is

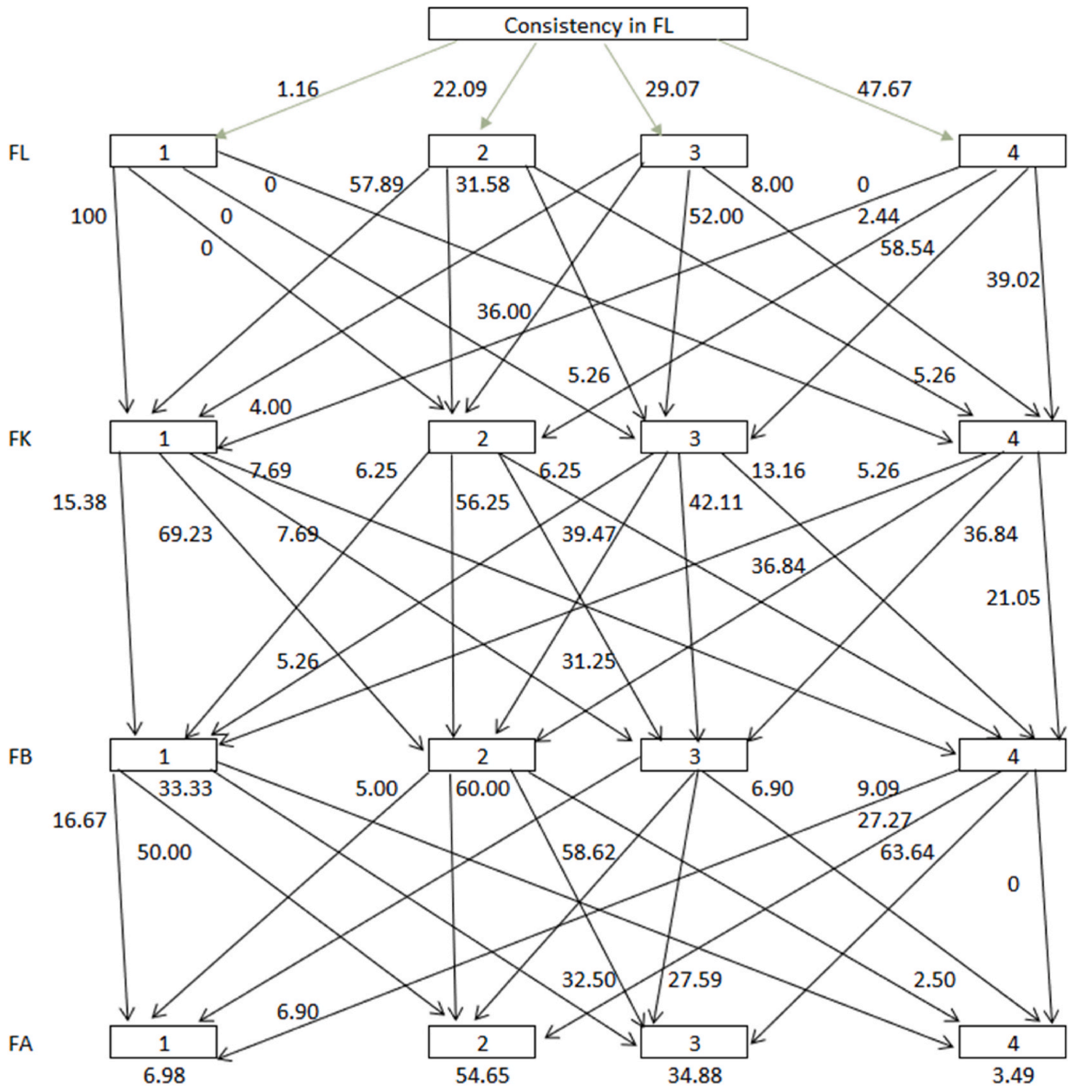


Fig. 2. Clustered male classes with intervals in Table 2. Source: Own elaboration.

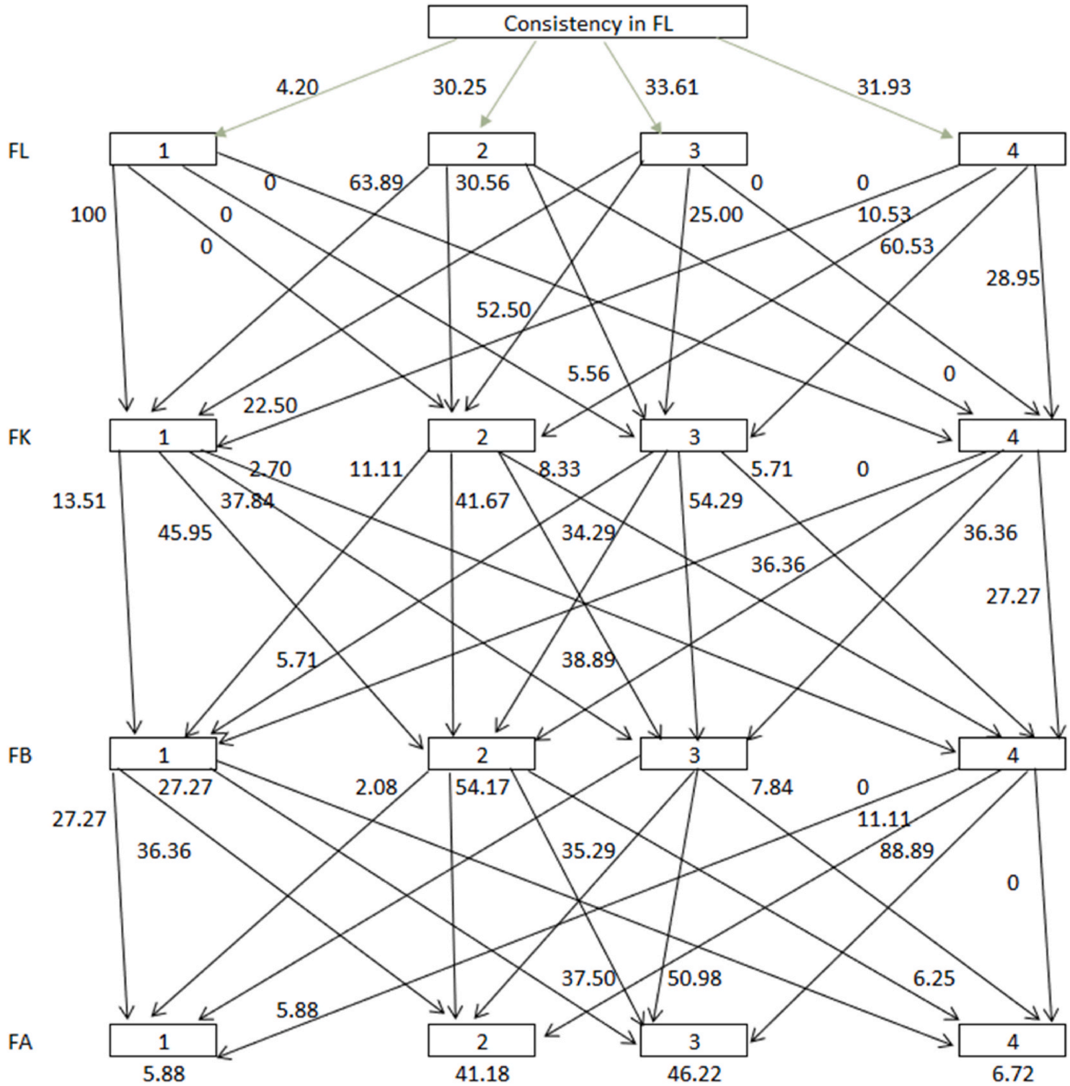


Fig. 3. Clustered female classes with intervals in Table 2. Source: Own elaboration.

no relationship between FB1 and FA4 among men. Consequently, although men are generally more knowledgeable and competent, women present a behavior-attitude assessment more inclined towards a medium-high level, as confirmed by the comparisons of the relative weight of FB and the overall weight of FA in Table 3. This observation may explain why the process produces more favorable weights for women than for men, as if the combination of FB and FA compensates for the lack of skills and knowledge among women. As a result, women might be less well prepared but demonstrate a greater sense of responsibility and caution in managing their finances. To investigate this relationship further, FL, FK, FB, and FA values were clustered against men and women, respectively, and two additional AHPs were implemented. Table 4 shows the clustering ranges based on gender, while Figs. 4 and 5 depict the respective AHPs.

When analyzing Table 4, it is evident that the clusters of women generally have lower values, indicating that they are distributed around very low to low values. However, the FB dimension, stands out as an exception to this phenomenon, confirming the observations discussed earlier.

The comparison of the AHPs depicted in Figs. 5 and 6 shows significant differences between women and men within their respective clusters. Specifically, women have zero correspondence between FL1-FK2 and FL1-FK3, whereas they exhibit higher correspondence between FL4-FK4. In contrast, men have a higher propensity to focus on financial issues, as evidenced by FK1 and FB4 not being equal to zero and a higher correlation between behavior and attitude.

For the sake of completeness, Table 5 shows the weights of the levels with respect to the clustering by gender. Although the weights are not comparable because they are constructed on different classes, women tend to have lower levels of financial literacy. This could be explained by a variety of factors, ranging from cultural to behavioral, such as less exposure to financial information, limited financial education or a lack of confidence in making financial decisions. Moreover, financial behavior is very different, with women

Table 3
Gender-differentiated version of Table 2. The weights are derived from the AHPs shown in Figs. 2 and 3.

Male	Female
Relative Weight FL	Relative Weight FL
1. 1.16	1. 4.20
2. 22.09	2. 30.25
3. 29.07	3. 33.61
4. 47.67	4. 31.93
Relative Weight FK	Relative Weight FK
1. 15.12	1. 31.09
2. 18.61	2. 30.25
3. 44.19	3. 29.41
4. 22.09	4. 9.24
Relative Weight FB	Relative Weight FB
1. 6.97	1. 9.24
2. 46.51	2. 40.33
3. 33.72	3. 42.86
4. 12.79	4. 7.56
Global Weight FA	Global Weight FA
1. 6.98	1. 5.88
2. 54.65	2. 41.18
3. 34.88	3. 46.22
4. 3.49	4. 6.72

Source: Own elaboration.

Table 4
Gender-differentiated version of Table 1. The clustering of FL, FK, FB, and FA was again carried out by dividing men and women.

Clustering code			**1**	**2**	**3**	**4**
Meaning			*Very Low*	*Low*	*Medium*	*High*
FL		M	(-2.08, 7.47)	(8.10,12.39)	(12.75, 16.69)	(17.02, 23.33)
		F	(-7.65, −2.06)	(1.94, 8.76)	(9.06, 14.39)	(15.00, 21.00)
FK		M	(-4.93, 0.12)	(1.04, 4.10)	(5.00, 7.03)	(8.00, 9.00)
		F	(-6.80, −3.78)	(-2.92, 0.16)	(1.05, 4.06)	(5.00, 9.00)
FB		M	(-6.87, −3.89)	(-1.94, 2.04)	(3.00, 5.02)	(6.00, 10.00)
		F	(-5.91, 0.050)	(1.03, 4.04)	(5.00, 6.03)	(7.00, 9.00)
FA	M		(-0.31, 1.67)	(2.00, 2.67)	(3.00, 3.67)	(4.00, 5.00)
	F		(-0.97, 1.33)	(1.67, 2.67)	(3.00, 3.67)	(4.00, 5.00)

Source: Own elaboration.

showing a greater focus on savings and budgeting.

In conclusion, the evaluation of the weights obtained with AHPs further motivates the need to investigate gender inequality in the financial context. Indeed, as observed, some combinations of FB and FA of women succeed in balancing low FK values and vice versa, high FK values may not always be effective with respect to men's behavior and attitudes.

3.3. Analysis of inconsistency in discount functions and FL

The next step in the data analysis to determine the inconsistency of FL involves integrating AHP weights with Markov chains. This integration involves defining the transition matrices based on the weights obtained for each AHP level. The initial transition vector for each level is equal to the local weight vector of the previous level. For instance, the probability of transitioning from an FL cluster to an FK cluster is defined by the matrix product of the weights at level 2 and the vector representing the weights of level 1. The procedure for the FK, FB, and FA dimensions is summarized in Figs. 6–8, respectively. The process of interpreting the AHP weights as transition probabilities is a tool that combines the relative importance of the criteria with state evolution. Thus, the final transition vectors, highlighted in purple in Figs. 6–8, quantify the likelihood of transitioning to the different states within the three dimensions of financial capability.

Once the three vectors π_{FK}, π_{FB} and π_{FA} were obtained, they were combined and aggregated with the OWA.

Thus, after obtaining the 64 combinations, the elements of each combination were arranged in descending order, since for a given weighted vector $\boldsymbol{w}$, $w_i \geq 0$, $\sum_{i=1}^{n} w_i = 1$, the OWA function [24] is defined as

$$OWA_w(x) = \sum_{i=1}^{n} w_i x_{(i)} = < \boldsymbol{w}, \boldsymbol{x}_{\downarrow} >$$

Where $\boldsymbol{x}_{\downarrow}$ denotes the vector obtained from $\boldsymbol{x}$ ordering the components in a non-increasing manner. The weighted vector $\boldsymbol{w}$ is defined as

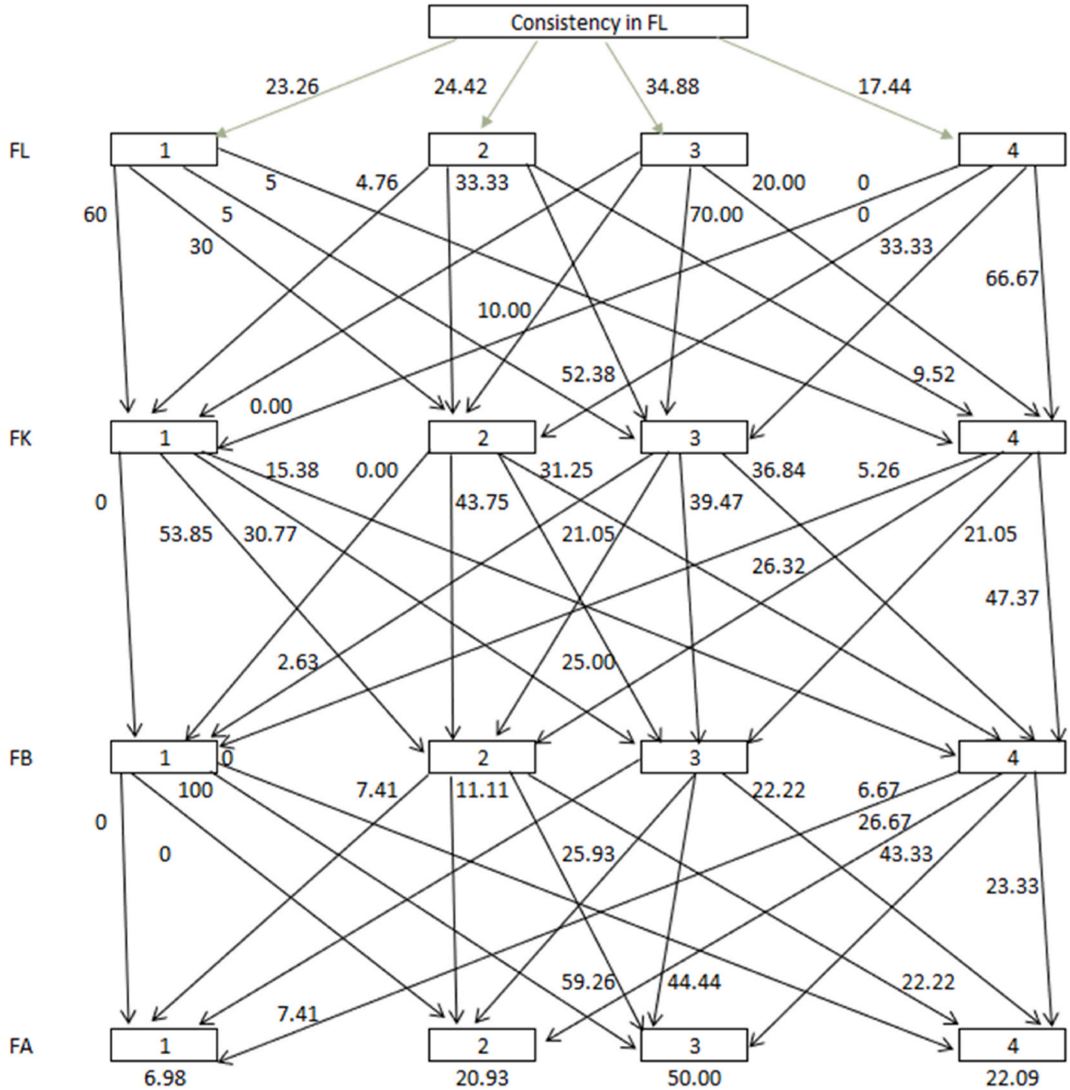


Fig. 4. AHP male clustering as Table 4. Source: Own elaboration.

[46]:

$$\begin{cases} w_i = \left(w_1{}^{n-i} w_n^{i-1}\right)^{\frac{1}{n-1}} \quad i = 2, \ldots, n-1 \\ \qquad w_n = \dfrac{((n-1)\alpha - n)w_1 + 1}{(n-1)\alpha + 1 - nw_1} \end{cases}$$

with the condition that w_1 is the unique solution in $\left(0, \frac{1}{n}\right)$ for the equation

$$w_1[(n-1)\alpha + 1 - nw_1]^n = ((n-1)\alpha)^{n-1}[((n-1)\alpha - n)w_1 + 1]$$

The weights were calculated by solving the equation for $n = 3$, and $\alpha = 1/2$, obtaining $w_1 = 0.330$, $w_2 = 0.333$, $w_3 = 0.337$. Table 6 shows the values of the four clusters of the combination aggregation, which are presented in Table 7.

At this point, it is possible to clarify the concept of inconsistency in FL dimensions as addressed in this paper. For example, let us consider the combination 111 and 422:

$$\sqrt{(\pi_{FK1} - \pi_{FB1})^2 + (\pi_{FK1} - \pi_{FA1})^2 + (\pi_{FB1} - \pi_{FA1})^2} < \sqrt{(\pi_{FK4} - \pi_{FB2})^2 + (\pi_{FK4} - \pi_{FA2})^2 + (\pi_{FB2} - \pi_{FA2})^2}$$

The inequation described should not be understood as a formal definition; rather it serves to convey that inconsistency among FL components refers to the degree of consistency in transition values across the three dimensions.

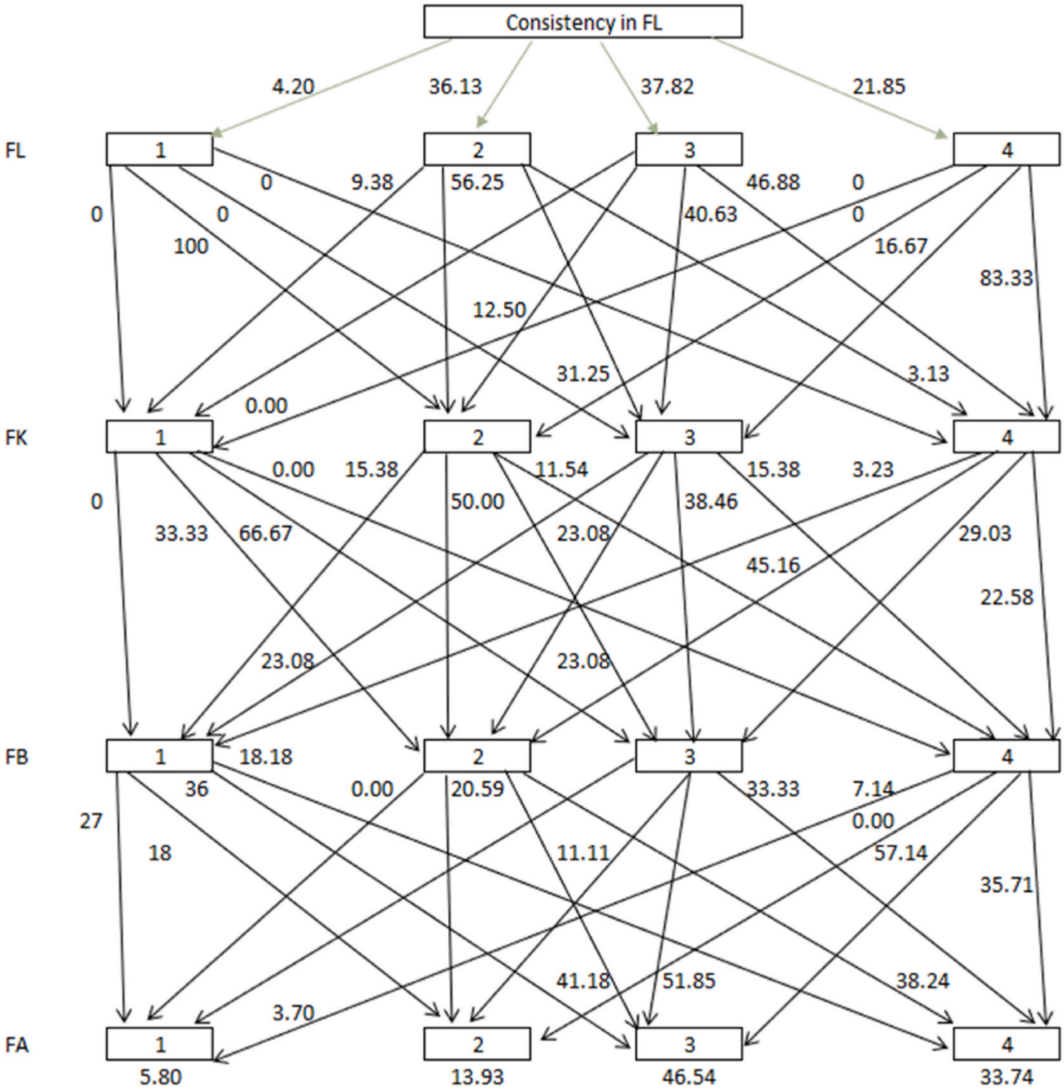


Fig. 5. AHP female clustering as Table 4. Source: Own elaboration.

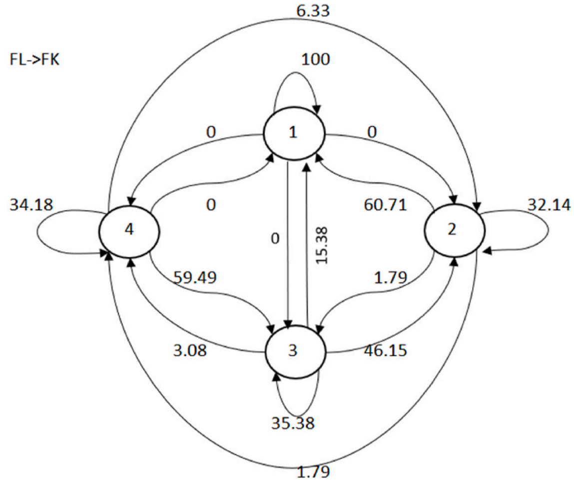
For each cluster, the discount function was constructed according to the procedure outlined in Ref. [18]. The median values of the discount function were calculated at various time points with respect to the four aggregation classes using OWAs. These values are shown in Table 8, while Fig. 9 displays the corresponding discount functions.

In order to calculate the highest degree of inconsistency among the four clusters, the exponential functions were derived to interpolate the discount functions. The results are displayed in Table 9 for values and Fig. 10 for graphical representation.

For each time point, the inconsistencies are computed as the variance between the exponential and interpolated discounting of the data, denoted as the disparity between the values in Tables 9 and 8 [18]. These values are presented in Table 10 and graphically displayed in Fig. 11, indicating a correlation between the OWAs clustering and increasing inconsistency, as shown in Table 11.

4. Discussion

The present work investigated the relationship between attitude in intertemporal choices and financial culture, delineating its three components: financial knowledge (FK), financial behavior (FB), and financial attitude (FA). The first important results can be observed from the clustering shown in Table 1. The "very low" score cluster in the first column exhibits notably small values, especially for FL and FB, (−7.65, −2.06) and (−6.87, −0.88) respectively. The presence of clusters defined by negative numbers underlines not only the low preparedness of the sample but also a significant presence of individuals struggling with behavioral problems when dealing with financial issues. Furthermore, cluster 1 is notably distant from adjacent clusters; for example, FL1 and FL2 exhibit a difference of over 3 points, highlighting the need for action to diminish this already wide gap. In this regard, Table 4, which expresses the clusters used in the analysis segregated by gender (Figs. 4 and 5), provides useful information for defining interventions aimed at bridging the gap in



$$\pi_{FL} = (2.91, 27.18, 31.55, 38.35)$$

$$A_{FK}^{FL} = \begin{array}{cccc|c} 1 & 2 & 3 & 4 & \\ 100.00 & 60.71 & 15.38 & 0.00 & 1 \\ 0.00 & 32.14 & 46.15 & 6.33 & 2 \\ 0.00 & 5.36 & 35.38 & 59.49 & 3 \\ 0.00 & 1.79 & 3.08 & 34.18 & 4 \end{array}$$

$$\pi_{FK} = A_{FK}^{FL}\pi_{FL}$$

$$\left|\begin{array}{cccc|c} 100.00 & 60.71 & 15.38 & 0.00 & 2.91 \\ 0.00 & 32.14 & 46.15 & 6.33 & 27.18 \\ 0.00 & 5.36 & 35.38 & 59.49 & 31.55 \\ 0.00 & 1.79 & 3.08 & 34.18 & 38.35 \end{array}\right|$$

2427		24.27
2573	->	25.73
3544		35.44
1456		14.56
10000		100.00

Fig. 6. Interpretation of FL weights as transition probabilities to FK. Source: Own elaboration.

Table 5
Gender-differentiated version of Table 2. Weights derived from the AHPs shown in Figs. 4 and 5, i.e., obtained from the clustering in Table 4.

MALE	FEMALE
Relative Weight FL	Relative Weight FL
1. 23.26	1. 4.20
2. 24.42	2. 36.13
3. 34.88	3. 37.82
4. 17.44	4. 21.85
Relative Weight FK	Relative Weight FK
5. 15.12	1. 3.39
6. 18.61	2. 29.25
7. 44.19	3. 30.30
8. 22.09	4. 37.06
Relative Weight FB	Relative Weight FB
1. 2.33	1. 12.69
2. 31.40	2. 39.49
3. 31.40	3. 31.42
4. 34.88	4. 16.41
Global Weight FA	Global Weight FA
1. 6.98	1. 5.80
2. 20.93	2. 13.93
3. 50.00	3. 46.54
4. 22.09	4. 33.74

Source: Own elaboration.

the overall study.

In particular, it can be observed that women significantly populate cluster 1 in Table 1. In fact, differentiating by gender, men do not present a very low level of FL with two negative extremes, but rather oscillate between −2.08 and 7.47. However, it is important to observe how the genders behave symmetrically with respect to the FK and FB dimensions: examining the first two columns of Table 4, it indicates that while women display a negative extreme extending to the 'Low' cluster in FK, men exhibit a similar trend in the 'Low' cluster of FB, −2.92 and −1.94, respectively. This result suggests that interventions to improve FL levels must consider gender differences as women face challenges due to knowledge gaps, whereas men are more prone to adopt inadequate behavioral approaches. This symmetry in FB is corrected in FA, where clusters based on gender are similar, probably related to the interaction between their respective strengths and weaknesses. However, the gender gap is also evident as the 'High' cluster consistently presents lower values for females than for males.

Returning to the general analysis expressed in Fig. 1, a noteworthy correlation between FL and FK can be observed: the total correspondence between FL1 and FK1, along with the absence of correspondence between FL4 and FK1, emphasizes the substantial influence of financial knowledge on the degree of FL. However, the link between FK and FB is more nuanced, as the weights are more heterogeneously distributed. Analyzing the AHP in Figs. 2 and 3, it is reaffirmed that, in general, women tend to exhibit better financial behavior: in fact, the weight between FK1 and FB3 is greater for women, while the relationship between FK4 and FB1 is non-zero for

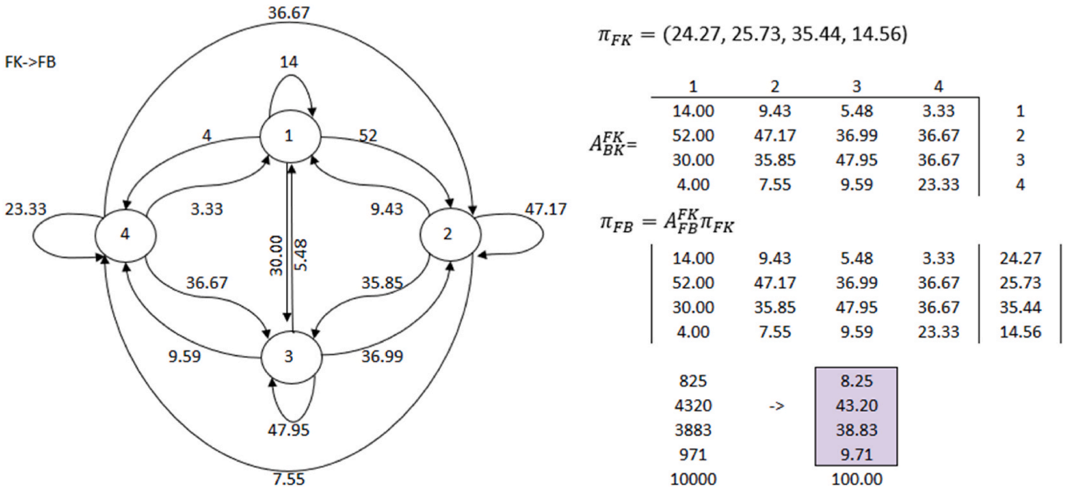


Fig. 7. Interpretation of FK weights as transition probabilities to FB. Source: Own elaboration.

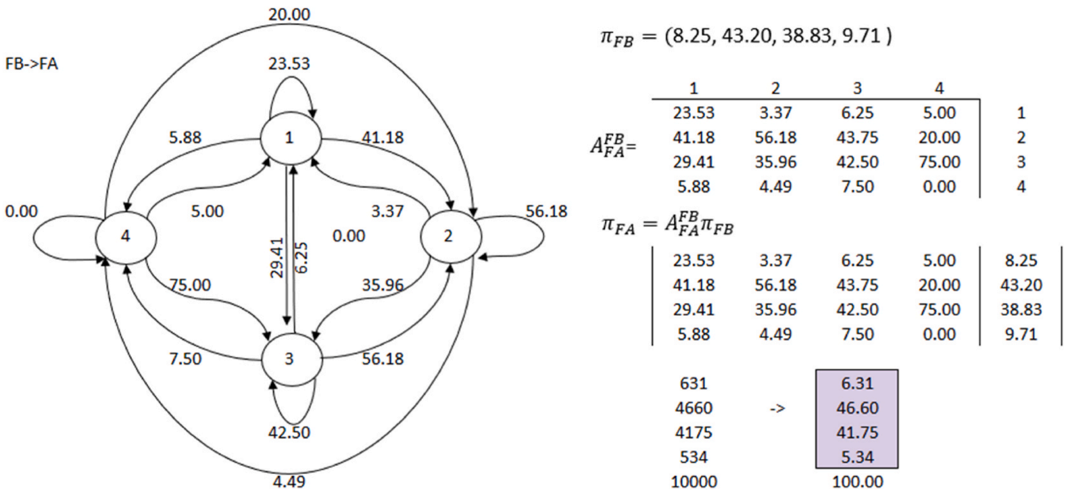


Fig. 8. Interpretation of FB weights as transition probabilities to FA. Source: Own elaboration.

Table 6
The 64 combinations of the three transition vectors were aggregated using the OWA operator and clustered into 4 classes, with the intervals shown.

Cluster OWA	min	max
1	9.35	17.05
2	19.46	25.12
3	25.61	31.60
4	33.05	41.67

Source: Own elaboration.

men. This underscores that a high level of FK does not ensure proper behavior or informed decisions in the financial context, highlighting significant points for varied interventions to improve individuals' FL status.

Finally, with respect to the final levels in Fig. 1, the link between FB and FA could be influenced by social and cultural factors. Regardless of gender, the "High" cluster of FB has a zero projection on the corresponding cluster of FA, indicating that attitude and behavior remain distinct dimensions of FL. The AHP analysis conducted with respect to gender-differentiated clusters confirms and enriches the aforementioned discussions. For example, comparing Figs. 4 and 5, the alignment between FK4 and FB4 is higher for women than for men (83.33 compared to 66.67).

Continuing the discussion of the results, the use of Markov chains made it possible to rewrite the weights obtained from Fig. 1 as

Table 7
Combination π_{FK}, π_{FB} and π_{FA} classes and the relative OWA cluster. For example, the combination (FK cluster 1, FB cluster 1 and FA cluster 1) belongs to cluster 1 of the aggregation.

OWA_1	111	114	141	144	211	214	241	244	311	314	341	344	411	414	441	444
OWA_2	113	121	124	131	134	143	213	221	224	231	234	412	413	421	424	431
	434	442	443													
OWA_3	112	142	212	242	243	312	313	321	324	331	334	342	343	433		
OWA_4	122	123	132	133	222	223	232	233	322	323	332	333	422	423	432	

Source: Own elaboration.

Table 8
Discount function values for each cluster of the aggregation with OWAs.

Time (days)	cluster 1_ OWA	cluster 2_OWA	cluster 3_OWA	cluster 4_OWA
0	1.00	1.00	1.00	1.00
2	0.94	0.91	0.91	0.87
4	0.89	0.67	0.71	0.67
7	0.82	0.50	0.63	0.50
10	0.69	0.43	0.56	0.40
14	0.62	0.37	0.37	0.33
20	0.69	0.29	0.29	0.29
30	0.49	0.22	0.25	0.23
45	0.44	0.17	0.20	0.19
60	0.51	0.13	0.21	0.16
90	0.40	0.10	0.22	0.13

Source: Own elaboration.

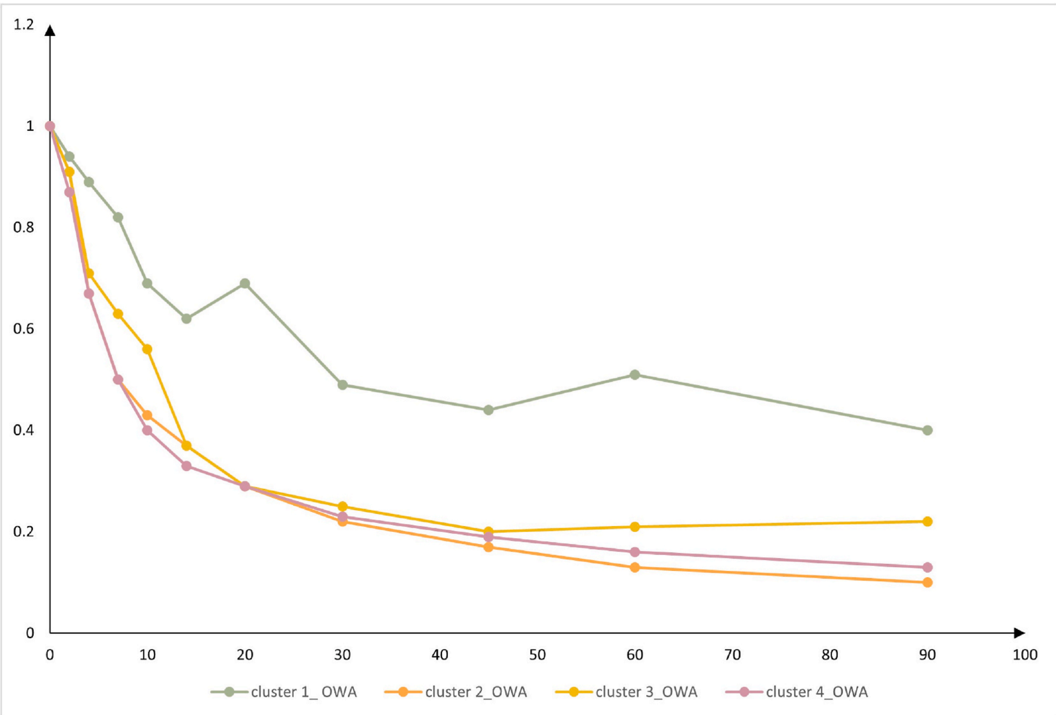


Fig. 9. Discount function for each cluster of the aggregation with OWAs.
Source: Own elaboration.

transition probabilities between clusters across the three FL dimensions. This representation holds robust descriptive power, enabling the monitoring of an individual's tendency to occupy a certain level in the next dimension based on the preceding one. Therefore, this description proves valuable for monitoring the efficiency of interventions aimed at financial literacy. Moreover, this approach enhances the OWAs' aggregation by imparting a sense of dispersion, delineating inconsistency among the characteristics of the three FL

Table 9
Exponential interpolation values for each discount function cluster of the aggregation with OWAs.

TIME (DAYS)	CLUSTER 1_ OWA	CLUSTER 2_ OWA	CLUSTER 3_ OWA	CLUSTER 4_ OWA
0	1.00	1.00	1.00	1.00
2	0.97	0.94	0.95	0.94
4	0.95	0.88	0.90	0.88
7	0.91	0.79	0.83	0.80
10	0.88	0.72	0.77	0.73
14	0.83	0.63	0.69	0.65
20	0.77	0.52	0.59	0.54
30	0.68	0.37	0.46	0.39
45	0.56	0.23	0.31	0.25
60	0.46	0.14	0.21	0.16
90	0.31	0.05	0.10	0.06

Source: Own elaboration.

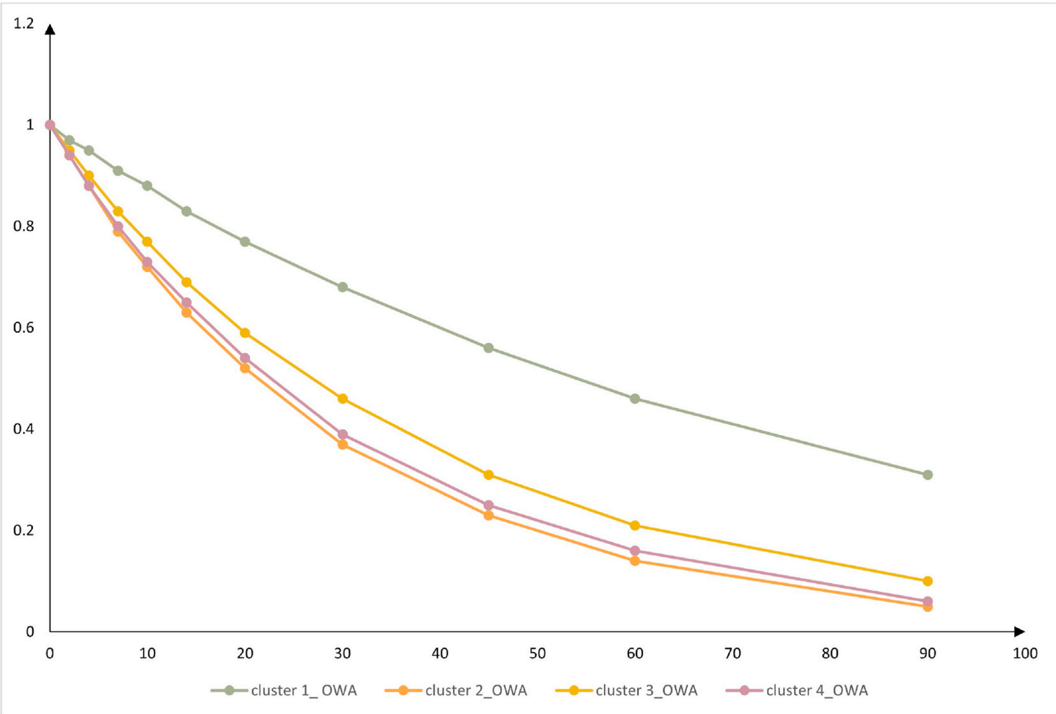


Fig. 10. Exponential interpolation for each discount function cluster of the aggregation with OWAs. Source: Own elaboration.

Table 10
Degree of inconsistency over time for each cluster of the aggregation with OWA. The values are obtained as the difference between Tables 9 and 8

TIME (DAYS)	CLUSTER 1_ OWA	CLUSTER 2_ OWA	CLUSTER 3_ OWA	CLUSTER 4_ OWA
0	0.00	0.00	0.00	0.00
2	0.03	0.03	0.04	0.07
4	0.06	0.21	0.19	0.22
7	0.09	0.29	0.21	0.30
10	0.19	0.28	0.22	0.33
14	0.21	0.26	0.32	0.31
20	0.08	0.23	0.30	0.25
30	0.19	0.15	0.21	0.16
45	0.12	0.06	0.11	0.05
60	−0.05	0.00	0.00	0.00
90	−0.09	−0.05	−0.13	−0.06

Source: Own elaboration.

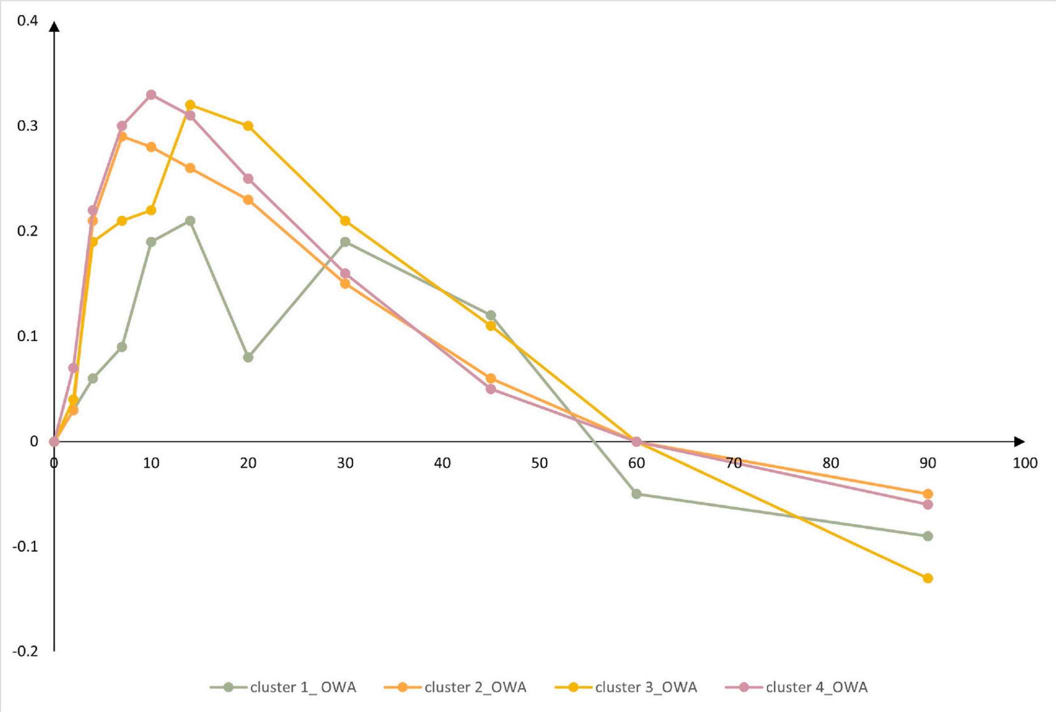


Fig. 11. Function of inconsistency for each aggregation with OWAs. Source: Own elaboration.

Table 11
Maximum degree of inconsistency for each aggregation with OWAs, i.e. the maximum value for each column in Table 10.

	cluster 1_ OWA	cluster 2_ OWA	cluster 3_ OWA	cluster 4_ OWA
Degree of inconsistency	0.21	0.29	0.32	0.33

Source: Own elaboration.

dimensions: the higher the aggregation score obtained with the OWAs, the greater the disparity between the components of π_{FK}, π_{FB} and π_{FA}.

The relationship between the aggregation of FL components and decision inconsistency reveals a correlation between choice quality and the interrelationship among FK, FB, and FA. It should be noted that a high level of FK, FB and FA does not necessarily guarantee consistent choices (as evidenced by the presence of combination 111 within cluster 1 of the OWA). Instead, it does indicate that while possessing a good level of FK, FB, and FA, decision consistency depends on how these dimensions interact. For example, the combination 333, which represents an average score across all three dimensions, is among those defining the highest time inconsistency.

The present research therefore emphasizes that in order to investigate the influence of FL on financial decision-making, it is necessary to decompose FL into its constituent components and individually project these dimensions onto individual choices.

With respect to the methodology used for the data analysis, it is important to highlight that the approach adopted was not statistical. This choice was deliberate to ensure a more dynamic and flexible description and interpretation of the sample, aligning it more effectively with the context at hand. Indeed, since the present study dealt with the relationship between the decision-making process and financial culture, which encompasses three distinct components, it was necessary to use an approach focused on individual preferences and their dynamism. The methodology selected for conducting the analysis was a combination of complementary tools that do not use statistical measures but break down individual preferences into a hierarchical structure and model them dynamically.

In particular, AHP defined a multilevel decomposition of the interaction among FL components and decision-maker characteristics. Markov chains provided a modeling of the hierarchical structure's weights with the dynamic depiction of individual preferences. OWA aggregated the input data with respect to the order of importance rather than their statistical distribution, while k-means allowed the clustering of heterogeneous and highly variable data.

In this context, the use of OWAs for the final aggregation of the transition weights underscores the motivation behind a non-statistical approach: unlike statistical analysis data that treats data uniformly, a survey of individual preferences and attitudes necessitates an aggregation procedure that considers the order of importance of the input data rather than their statistical distribution. In this way, the survey proved to be rich in details delineating the interaction between the behavioral mechanisms underlying the decision-making process and the interaction among the components of financial culture.

The strength of this study encompasses two aspects: one methodological and the other practical. Methodologically, the combined approach used – discussed earlier – was able to quantify the interaction among the three FL components, facilitating qualitative assessments that were not known a priori. However, describing the weights of the FK, FB, and FA dimensions through the Markov process preserved the dynamism relating to human character, which is indispensable for investigating the development of individual preferences in the context of intertemporal choices.

Practically, the present research contributes to the investigation of the relationship between decision-making and FL, highlighting the need for personalized interventions to improve the decision-maker's individual condition, necessary to increase their effectiveness. For example, the extensive discussion on gender differences has shown how differences between men and women manifest across the three FL components. Similarly, any type of characteristic, such as age or academic education, could be examined to further delineate the link between decision-making and financial culture [17]. Moreover, to the best of our knowledge, this is the first study to relate decision consistency in the context of intertemporal choices to the consistency of FL's three constituent components.

It is important to highlight that since this is a multi-method study, its limitations are determined by the structural limitations of the AHP and Markov chains. In particular, AHP is highly sensitive to input data and therefore small variations could lead to significant differences in the results. Overcoming this limitation could involve the introduction of fuzzy multi criteria methods [47] for more nuanced and thus even better descriptions of individual characteristics. Markov chains, on the other hand, do not allow a temporal description of the state, therefore requiring repetition of the entire methodology over several time periods to obtain discrete descriptions. While OWAs offer unified interpretation of input data, they emphasize data arrangement to study their interaction. It would therefore be interesting to repeat the analysis with alternative aggregation operators, based on approaches directed at other characteristics of the input data, to enrich the assessment of the relationship between financial decision-making processes and financial culture.

5. Conclusion

This paper aims to investigate the relationship between the degree of financial literacy and the phenomenon of inconsistency in intertemporal choices. The focus is on understanding how FL components influence decision-making in uncertain scenarios, in order to assess whether a high degree of FL can ensure consistent decision-making. Indeed, intertemporal preferences are excellent descriptors of the decision-maker's attitudes towards the uncertainty of the future, an important feature of the financial decision-making environment.

To achieve this aim and to obtain rich descriptions of the FL components, interviews were conducted through the construction of a website, presenting two questionnaires: the first aimed at defining the FK, FB, and FA scores, while the second sought to determine the trend of the individual discount function. The data were analyzed by combining different methods: AHP made it possible to investigate the FL components by categorizing individuals into 4 clustered classes via the K-means algorithm of FK, FB and FA levels. Markov chains were used to dynamically depict the weights obtained from AHP, generating transition vectors indicating the probability of transitioning between different level classes. Finally, OWAs made it possible to aggregate the values of π_{FK}, π_{FB} and π_{FA} combinations, defining an output expressing their coherence. The measure of inconsistency in intertemporal choices, on the other hand, as defined in Ref. [18], relies on the disparity between exponential and empirical preferences.

Our sample exhibited low to medium levels of financial literacy. The use of AHP was fundamental in defining important qualitative results with respect to the FL components.

As expected, a strong correlation existed between financial knowledge and financial literacy. However, in terms of behavior, a high level of financial knowledge did not correspond to adequate behavior, nor did it translate into positive attitudes.

Upon examining the results based on gender, it becomes evident that women show a lower degree of financial knowledge, men tend to demonstrate better financial behavior regardless of their knowledge. Women exhibit greater alignment between knowledge, behavior, and attitudes, resulting in more favorable weights compared to men. Consequently, despite having less financial preparation, women tend to manage their finances more responsibly and carefully. In addition, women show a greater focus on savings and budgeting.

The lower levels of financial literacy among women may be explained by a variety of factors, ranging from cultural to behavioral aspects, such as less exposure to financial information, limited financial education, or a lack of confidence in making financial decisions.

With regard to the second part of the analysis, however, a correspondence was found between the degree of inconsistency and the clusters in Table 10. These clusters were obtained by aggregating all possible combinations of the transition probabilities obtained in Figs. 6–8 using OWAs. This approach provided a measure of congruence among the dimensions comprising FL. Aggregating with OWAs captures the complex nuances in the data, highlighting decision-making weaknesses among individuals who lack skills related to specific FL dimensions.

Comparing Fig. 10 and Table 11, one can discern the difference between an exponential discount function reflecting greater impatience and a hyperbolic discount function indicating a greater degree of inconsistency. The former does not necessarily maintain a relationship with respect to inconsistency in FL dimensions; impatience expresses a preference for more immediate results but is not an indication of non-rational choices. Conversely, the latter reflects a discrepancy between beliefs, emotions, evaluation skills, planning and self-control.

The practical implications of this research are situated within the framework of MiFID (Markets in Financial Instruments Directive). MiFID aims at a better understanding of customer characteristics and needs in order to ensure appropriate services and customized interventions. Likewise, regarding policy implications, the results of this research are useful to identify different groups where public interventions are needed. This identification is crucial for implementing customized financial education programs, ultimately improving citizens' personal finances and, consequently, their general well-being. Therefore, the profiling process necessitates a detailed description of clients' financial literacy in order to understand potential gaps that might contribute to non-rational choice behavior. In fact, despite observed instances, where good knowledge does not always imply sound financial behavior, this inconsistency must be taken into account by financial advisors.

This study not only collects interesting qualitative profiling results but also introduces a methodology for decomposing the multiple factors influencing individual decision-making. In addition, the findings, particularly those addressing gender differences, highlight the importance of diversifying support interventions to promote higher levels of financial literacy. In this regard, it becomes crucial to acknowledge gender disparities not to compensate for them but rather to leverage them effectively to narrow the gap [48].

Future studies could focus on improving the analysis, in particular with respect to the clustering algorithm and the aggregation techniques used. Furthermore, in delving deeper into the underlying factors influencing decision-making, future research might incorporate elements such as marital status, academic background, and age within the hierarchical evaluation [17]. Finally, the discussion regarding the limitations of the methodology, as previously addressed, proposes several lines of development that could be a guide for improving this approach and obtaining qualitatively and quantitatively richer results.

Ethics statement

Ethics approval number for our study: UALBIO2023/009 provided by Comisión de Bioética de la Universidad de Almería.

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Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Data availability statement

The data that has been used is confidential.

CRediT authorship contribution statement

Viviana Ventre: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Roberta Martino:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **María José Muñoz Torrecillas:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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