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An Analytic Network Process to Support Financial Decision-Making in the Context of Behavioural Finance

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Abstract: Following the financial crisis of the last decade and the increasing complexity of financial products, the European Union has introduced investor protection tools that require professionals to carry out a client profiling process. The aim is to offer products that are in line with the characteristics of the individual. The classes of variables for comprehensive profiling are obtained by matching the elements proposed by the Markets in Financial Instruments Directive and studies of classical finance. However, behavioural finance studies, which emphasise the importance of behavioural attitudes, are not clearly considered in this structured profiling. The present paper discusses the implementation of an analytic network process to support financial decision-making in a behavioural context, combining regulatory guidance and qualitative and quantitative evidence from the literature. The Kersey Temperament Model is used as the behavioural model to construct the network cluster that incorporates personality into the valuation. Uncertainty management is incorporated through recent studies in the context of intertemporal choice theory. The functionality of the network is verified through a case study, where two alternatives with different characteristics are considered to meet the same investment objective. The present approach proves how the generated structure can provide strong support for financial decision-making.

Keywords: analytic network process; behavioural finance; decision-making; intertemporal choice; MiFID II; temperament theory

MSC: 91B06

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1. Introduction

Financial decision-making is a complex process in which individuals must evaluate several options and make the best choice in accordance with their goals, constraints, and resources. Classical finance theory assumes a rational decision-maker capable of considering all the variables that characterise an investment portfolio. Over the years, the increasing complexity of financial products and the global crises that have enveloped the financial sector have questioned the effectiveness of standard financial theory, which seems to have a limited role in discussing problems such as: How do individuals choose their portfolio? How do they process complex information? [1].

Behavioural finance is a field of research that has emerged as a complement to the limitations of classical finance to reduce the gap between investors' expectations and actual behaviour. Behavioural finance uses cognitive psychology to study the mechanisms of financial decision-making, aiming to understand and explain the empirical behaviour of individuals: only by understanding how individuals and markets behave can better results can be achieved [2]. Ref. [3] notes that understanding the behavioural decision-making process helps both individual investors and investment planners to understand their own and their clients' behavioural biases when making investment decisions.

The change of focus from the "financial environment" to the "agent of the financial environment" [1] motivated regulatory interventions aimed at customer protection and safeguarding. The Markets in Financial Instruments Directive II (MiFID II) is a European directive that gives special attention to client profiling in the context of financial advice with the aim of prescribing the best possible financial instrument to the client. Since it is difficult for an investor to assess a market with complex features and products, financial intermediaries must guarantee a correct and efficient advisory service. By cross-referencing MiFID II indications and studies in the literature, the information required for client profiling can be grouped into five classes: socio-demographic characteristics, experience and knowledge, financial situation, investment objectives and risk tolerance [4]. Anyway, the behavioural component emphasised by behavioural finance is only expressed by risk tolerance. As Pompian [2] points out, the assessment of risk from a behavioural point of view requires the division of risk into risk appetite and risk tolerance: the former is the propensity to take risks, and the latter is the ability to take risks. These risk levels vary between individuals and, as is reasonable to assume, an investor might have a high level of risk appetite but a low level of risk capacity. From a behavioural point of view, the difference can be understood by differentiating between known and unknown risks: when the risk goes beyond what is known, behavioural problems begin [5]. At this point, within the evaluation framework of customised strategies with respect to the client, the concept of uncertainty becomes necessary for a more comprehensive assessment of the individual's attitude. Risk and uncertainty are very different concepts: risk involves an unknown result but a known distribution, while uncertainty involves both an unknown result and a known distribution [6]. Over time, these differences were forgotten and ignored in favour of the formalisation of apparently accurate models. The idea that one needs to work with market predictions by incorporating the knowledge that the future is radically uncertain was only discovered after the global financial crises and research in behavioural finance.

The introduction of an additional class for client profiling, i.e., the uncertainty management class that cannot be included in the risk tolerance class, makes the decision-making process for selecting appropriate strategies for the investor even more complex.

The present paper discusses the implementation of an analytic network process (ANP) [7] that can support financial decision-making by including behavioural aspects in the evaluation. Previous works [2,8] offered a deep and careful guide to contrast the negative effect of behavioural biases on financial decisions, useful for individual investors and financial advisors. The aim is to extend this approach and to reinforce it from a decision-making perspective through the following strengths. Firstly, from a technical point of view, the ANP is an advanced decision support methodology that enables the modelling and analysis of complex interconnections between elements in a large and sophisticated decision network. This feature makes it possible to include dependency and interdependency relationships between the five customer profiling classes mentioned above and the behavioural aspects [9–11]. In particular, the behavioural model used to construct the network cluster incorporating personality into the assessment is the Kersey Temperament Model (KTM) [12]. The latter, in fact, besides being in general a reference model for research in behavioural finance [13], was also used by Pompian [14] for the definition of Behavioural Investor Types (BITs) [15]. Secondly, from an evaluative point of view, two innovative aspects are included in the analysis of alternatives with respect to the profiling of the individual. On the one hand, uncertainty management is included through recent studies in the context of intertemporal choice theory [16–18], in which uncertainty is generated by the indeterminacy of the future. On the other hand, the structure of the ANP allows more nuances of the individual's behavioural aspect to be included, so that not only Kersey's primary temperament is considered, but the scores of the other temperaments will also be considered simultaneously.

The functionality of the network is tested by a case study in which, assuming two alternatives equally satisfying an investment objective, the choice will be defined by the inclusion of Kersey's temperament test scores for the client and by the individual attitude towards risk and uncertainty. For the implementation of the case study, some network weights are statistically constructed through a survey involving 200 individuals, other weights are defined by the evaluation of 2 experts who agree on the scores and, finally, other weights are constructed from client preferences.

To the best of our knowledge, the present paper is the first to discuss the use of the ANP to improve financial decision-making in the context of behavioural finance. As will be proven, the proposed methodology enriches assessments and enables informed choice.

To achieve the aforementioned aims, the article will present all the necessary tools for understanding the methodology and application. In particular, the second section introduces the AHP and the ANP, highlighting their structural components. Subsequently, with respect to an analysis of the main elements of strategic customisation, the authors propose possible implementations of the network structure in the context of behavioural finance. Before concluding Section 2, the authors provide the basic elements and methodology for understanding the derivation of decision weights, which are necessary during implementation. Section 3 is completely dedicated to the case study, from the construction of the network structure to the completion of the decision weights and the definition of the best alternative. After setting out the investment objective and possible strategies, the authors present the structure of the ANP and the questionnaire used to collect the empirical data. In particular, all possible inter- and intra-connections between the quantities derived from the questionnaire are described and discussed in order to characterise the implementation network. The process of inserting the weights also makes it possible to extrapolate information that the experts themselves considered during their own evaluations; this paragraph emphasises the importance of strategic customisation and the effectiveness of a network structure that allows several combinations to be taken into account simultaneously.

Section 4 discusses the results and comments with respect to the initial aims. The authors also provide possible future studies that can improve the performance of the methodology.

Finally, the Conclusion section presents the major results and discusses them in comparison to other approaches used in the context of uncertainty. In this section, the authors comment on the applicability of the study and the flexibility of the network structure, highlighting its usefulness and originality in the literature.

The paper is developed as follows: the second section clarifies the method and the materials used, i.e., the application of the ANP in the context of behavioural finance; the third section discusses the application to the case of a client who has to select an alternative for his or her investment objective; and the discussion and conclusion sections follow.

2. Materials and Methods

2.1. Analytic Network Process

Mathematics provides models that can support decision-making by analysing and solving complex problems, considering external constraints and uncertainties related to variables beyond the decision-maker's control. In the context of financial decision-making, which by its nature involves conflicting objectives such as the risk minimisation and maximisation of portfolio financial performance, a multi-criteria problem arises. Recently, several studies have extensively reviewed the academic literature on multi-criteria decision-making (MCDM) techniques applied to portfolio selection [19]. The analytic hierarchy process (AHP) of Saaty [20,21] and the analytic network process (ANP) of Saaty and Vargas [7] represent multi-criteria techniques for decision support. These methodologies make it possible to analyse alternatives with factors and criteria that are difficult to compare directly. The ANP represents a generalisation of the AHP and allows for addressing complex decision-making problems that go beyond the traditional hierarchical structure. The ANP allows for modelling interconnections and loops that would not be manageable with the AHP. Therefore, a network structure, rather than a hierarchical structure, is more appropriate to deal with the categories defined by the MiFID II regulations and classical finance. Looking at the structure of the ANP and the AHP in Figure 1, it is possible to observe that the relationships expressed by the former do not have a top-down form but have a cyclic form defined by the connections and interconnections between their elements.

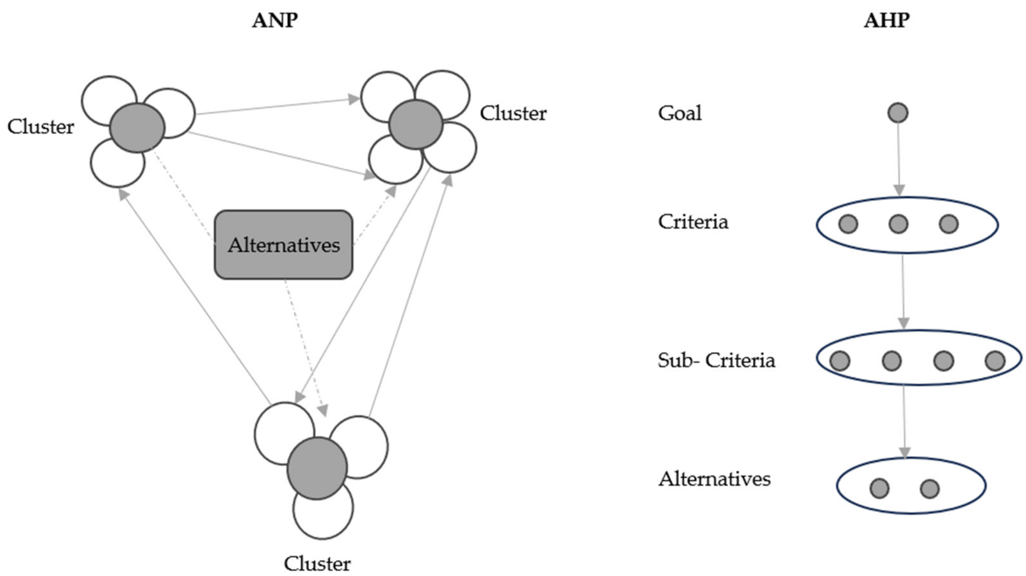

Figure 1. Graphical representation of the analytic network process (ANP on the left of the figure) and the analytic hierarchy process (AHP on the right of the figure): it can be seen that the network structure allows many more combinations to be considered during the decision-making problem than the hierarchical structure.

The analytic network process (ANP) offers an advanced perspective to approach decision-making using a system of pairwise comparisons to measure the weights of the components of the structure and rank the alternatives [22]. In the details of the ANP method, the first stage involves structuring the decision problem, an example of which is shown in Figure 2. After identifying the objective to be achieved (goal), the problem is divided into nodes—elementary parts that influence the development of the problem. The nodes are aggregated into homogeneous clusters, known as alternatives clusters (the possible solutions to the problem) and criteria clusters. Subsequently, the nodes and clusters are interconnected, revealing dependencies and interdependencies. Within the framework of problem structuring, there are two types of models: the "single" network model and the "complex" network model. The former is a free modelling approach, where clusters and nodes are interconnected, reflecting dependencies and interdependencies; the latter follows a BOCR (Benefits, Opportunities, Costs, Risks) logic scheme, which allows for a comprehensive analysis of the positive and negative aspects of the decision over time [23,24].

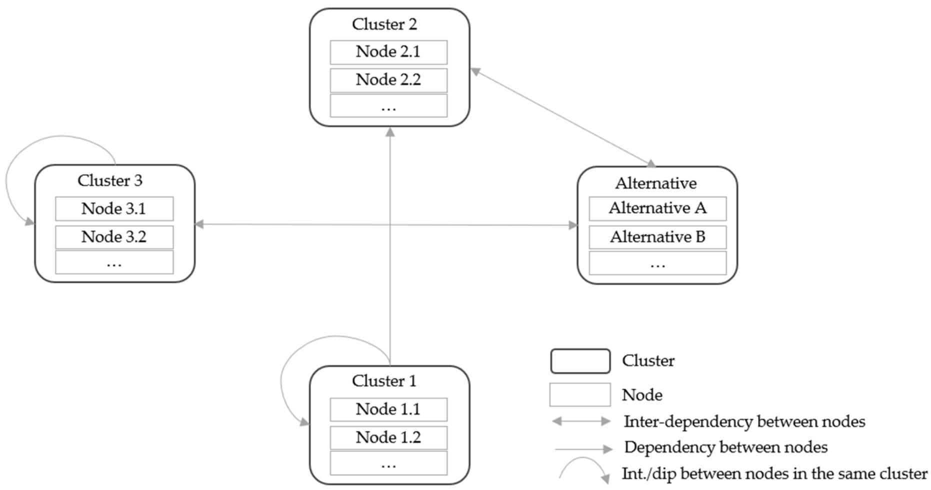

Figure 2. General structure of ANP.

In general, precisely because of the absence of method, the single network model is more complex to construct but allows for a greater expression of the decision elements.

The second step is the calculation of the priorities of network elements and alternatives, for which the comparison method is used. This involves pairwise comparisons, where the relative importance of elements in relation to a parent element is established. Judgements are made according to Saaty's [25] absolute number scale, which translates verbal judgements into numerical ratings. In pairwise comparisons, a preference must be established between the two child elements, compared in relation to the parent element.

The comparison values are entered into a square matrix $n \times n$ characterised by having the number 1 on the main diagonal of the matrix and by the property that the elements above and below the diagonal are reciprocal. The resulting priority matrices are used to construct the unweighted, weighted and limit supermatrices, represented in Figure 3.

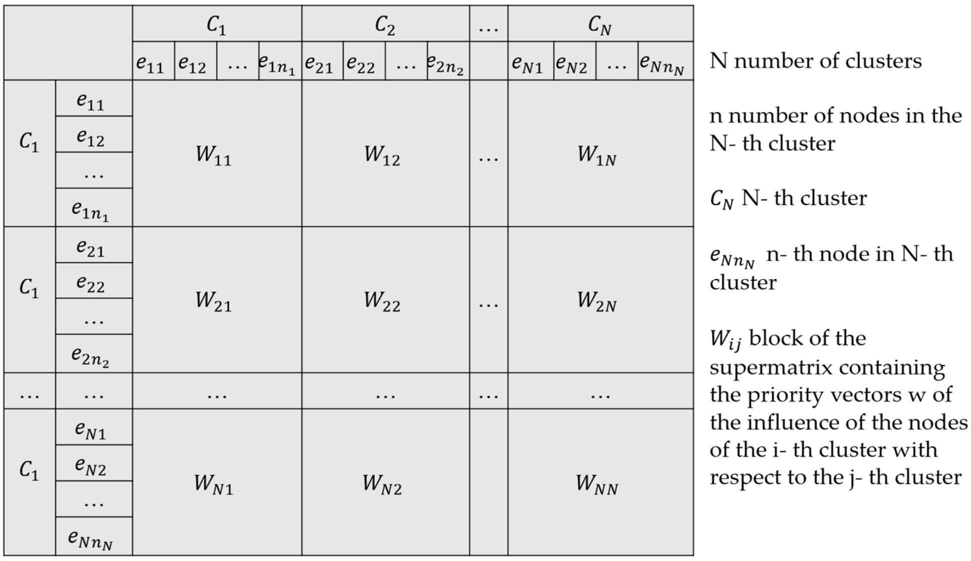

Figure 3. Generic supermatrix obtained in an ANP.

These supermatrices, the study and construction of which is the third fundamental step of the ANP, represent the relationships within the network model and the assigned priorities. The null blocks of the supermatrix express the absence of relationships: the unweighted supermatrix contains the priority vectors obtained in the second step; the weighted supermatrix is obtained by multiplying the unweighted supermatrix with the matrix expressing the weight of the clusters; the limit supermatrix is obtained as $\lim_{k \to \infty} W^k$, where W is the weighted supermatrix and contains the final priority vector. Finally, as a fourth step, the final priority vector is normalised, identifying the best alternative.

To support the implementation of this method, the software SuperDecisions Version Windows V3.2 [26] by Creative Decisions Foundation, 4922 Ellsworth Ave, Pittsburgh, PA 15213, USA is used, simplifying the structuring of the problem and the visualisation of the results.

2.2. *Analytic Network Process to Support Financial Decision-Making*

The guidelines set by MiFID II are essentially experience and knowledge, financial situation, and investment objectives. The literature enriches these guidelines by including risk tolerance and socio-demographic characteristics in the profiling. The set of classes and variables are listed in Table 1 [4].

Table 1. Indications on the questionnaire according to the regulatory framework and literature.

Regulatory Framework		Literature	
Classes	**Variables**	**Classes**	**Variables**
Socio-demographic characteristics	Not planned	Socio-demographic characteristics	• Civil status • Family status and dependents • Gender • Age
Experience and knowledge	• Profession • Education • Nature, volume, and frequency of financial transactions by the client • Services, transactions, and financial products with which the client is familiar with	Experience and knowledge	• Profession • Education • Previous experience in investments and positive or negative outcomes • Knowledge of the functioning of financial markets and of certain terminologies such as trade-offs, risk return, diversification portfolio. . . • Knowledge of financial products • Overconfidence and optimism
Financial situation	• Regular income information • Regular financial commitments • Information on investments, assets, and movable property	Financial situation	• Regular income information • Regular financial commitments • Information on investments, assets and movable property • Other financial commitments, including projected commitments and expectations of changes in regular expenditures
Investment goals	• Desired retention time of the investment • Investment goals • Preferences and risk profile	Investment goals	• Desired retention time of the investment • Investment goals • Preference towards time • Liquidity needs • Amount of investment best in relation to wealth or income
Tolerance to risk	• Not expected, included in the investment objectives	Tolerance to risk	• Attitude toward risk (objective risk) • Emotional ability to take on risks (subjective risk) • Awareness of losses

From a structural point of view, the five classes discussed in Table 1 constitute the network clusters, while the nodes are the variables. Some dependencies and interdependencies that can be included are:

- Internal relations between variables of class "experiences and knowledge" and relations between class "experiences and knowledge" and "sociodemographic characteristics". In fact, some studies indicate that these parameters are interrelated, and therefore the authors consider it appropriate to include their mutual weights in the proposed ANP [11];
- To consider the extent to which investment objectives should meet the personal needs of the decision-maker, the relationship between "financial situation" and "investment goals" could be included in the profiling process;
- Include a dual relationship between "alternatives" and "investment goals" to consider the possibility that available alternatives may also affect investment goals.

To improve profiling, behavioural finance research, which highlights the importance of cognitive and behavioural attitudes in obtaining a rich description of the decision-maker, should be added to the previous five classes [27]. In addition, recent research has demonstrated a quantifiable cognitive dimension when evaluating temporal alternatives under uncertainty [18,28,29]. Thus, other clusters can be included and implemented to include behavioural finance studies and the dimension of uncertainty in decision-making. In particular, the behavioural characteristics are included in Kersey's temperament clusters, which are Artisan, Idealist, Rational and Guardian. The main advantage of the Kersey Temperament Model (KTM) is that the classification focuses more on behaviour than on preferences, and this can help in understanding individuals [30]. Furthermore, the KTM can capture 42 scales observed in temperament theory [31], and the classification is based on an understanding of what individuals are able to do well in different circumstances [12].

Uncertainty management, on the other hand, is expressed through two measures defined in the context of intertemporal choices. The first measure refers to the degree to which impatience decreases [32], through the hyperbolic factor—an index defined by Rohde [33]. The degree to which impatience decreases over time is behaviourally related to emotional drives that intervene during decision-making and result in anomalous preferences [18]. The second measure, on the other hand, is a measure of the decision-maker's non-rationality obtained as the distance between empirical and exponential preferences [28,34]. This measure is expressed in relation to the subjective perception of time and quantifies the degree of uncertainty aversion. By including the cluster of temperaments, decreasing impatience and uncertainty aversion, the researchers can discuss interesting relationships and interrelationships that highlight the functionality of a network structure:

- Kersey's temperaments are related to the investment goal and alternatives in that temperaments have been seen to affect financial decisions, how decision-making is developed and how financial information is analysed [27,35,36];
- Temperaments are related to risk; for example, Guardians have a lower risk tolerance than Rationales and Artisans, generally characterised by a higher risk tolerance [30,37];
- Temperaments are related to the degree to which impatience and the degree of uncertainty aversion decrease as they relate to behavioural biases [38] that underline anomalous preferences [29];
- Temperaments are related to individual characteristics in that temperaments of different genders have different characteristics [39];
- Risk tolerance is related to uncertainty aversion and the degree of decreasing impatience to express how uncertainty management could affect risk tolerance, and vice versa;
- Uncertainty aversion and the degree of decreasing impatience are related because they are both different characteristics of a discount with a non-exponential trend [28].

The connection between "risk tolerance" and the quantities related to uncertainty management is considered because, in the classical theory context, risk is understood as a precise parameter calculable by quantitative methods [40]. However, this objective view of risk fails when one considers the absence of two necessary assumptions: first, the assumption of an efficient market, a condition denied by empirical evidence [41]; second, the behaviour envisaged by the classical theory corresponds to the profile of a perfectly rational decision-maker. Thus, beyond the behavioural assessment of empirical evidence, risk perception also involves subjective factors and psychological attitudes. Specifically, heuristics, biases and psychological characteristics also influence risk perception [42]. In addition, experimental evidence has shown that loss aversion is also related to neurological factors [43,44], which in turn are related to intertemporal choice behaviour [45].

At this point, the authors point out that further interactions and relationships between clusters or between clusters and nodes to be added to the network may vary depending on the specific case. The network structure allows enough flexibility to improve the structure with respect to the case at hand, supporting even more specific decision-making. Figure 4 represents a possible implementation of the structure discussed so far.

2.3. Determination of Weights

In all nodes, the comparison is made by comparing the elements in pairs, so if there are n elements to compare, $n(n-1)/2$ judgements are made. Weights can be determined in different ways using the software [26]. After selecting the clusters or nodes to be compared, the modes for determining the weights are graphical, verbal, matrix, questionnaire and direct. Briefly: direct mode allows the weight of individual elements to be entered directly; graphical mode allows the weight to be entered in correspondence to the length of a bar; verbal mode involves the use of words corresponding to Saaty's fundamental scale, shown in Table 2; matrix mode provides that each cell of the matrix corresponds to the pair of elements to be compared, and judgements are displayed as decimal numbers rounded to the nearest tenth; and finally, the questionnaire allows one to select the numerical judgement—from those shown in Table 2—that best expresses the judgement by answering a comparison question such as "how much is element i more satisfactory/important/preferred than element j with respect to the node/cluster?".

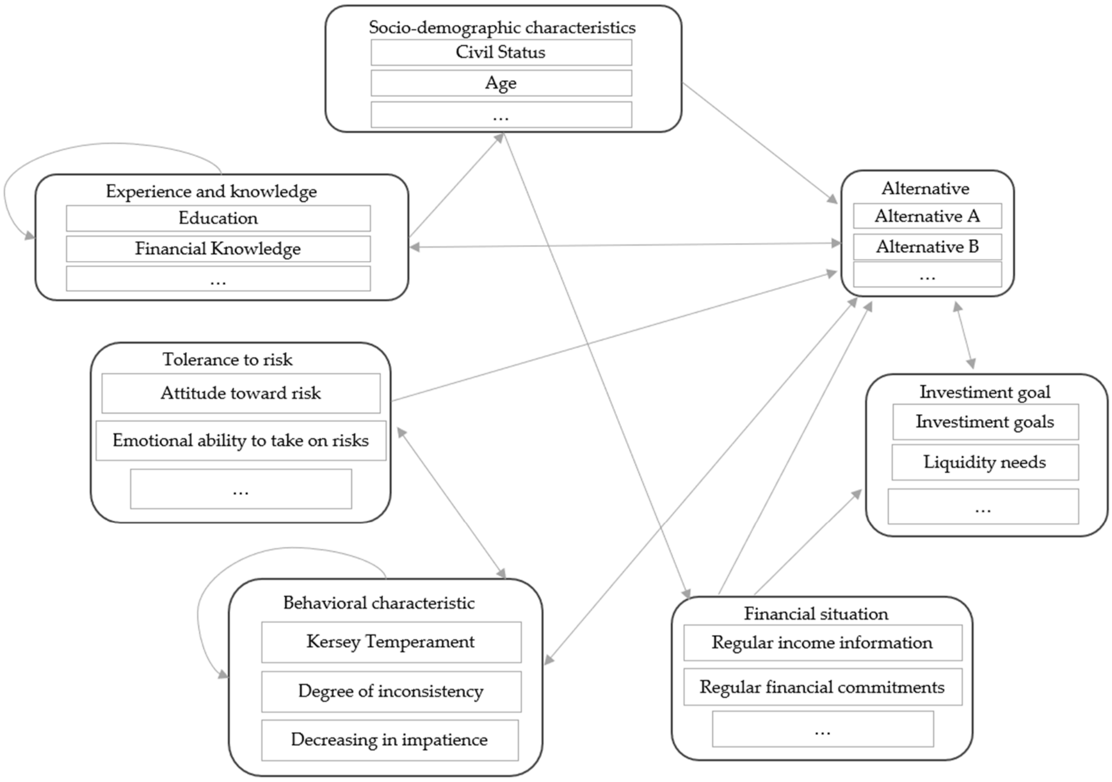

Figure 4. Network structure obtained by crossing the indications for customer profiling found in the literature and the regulatory context discussed and presented in Table 1, and the behavioural context. Among the main elements of the ANP, it is possible to observe how behavioural characteristics are in connection with risk tolerance, being distinguished in order to emphasise the importance of simultaneously considering uncertainty and risk in a different way in the financial decision-making problem. The other connections and interconnections have been discussed in the text, but the reader should bear in mind that among the positive aspects of the ANP, in particular its flexibility, allows the structure to be adapted for each specific case.

To complete the network weights shown in Figure 4, the present paper proposes to use different methods (direct, questionnaire and matrix) depending on the cluster or node under consideration. This approach makes it possible to combine weights defined by expert judgement; weights defined by the frequency of a given combination in a set of individuals, as proposed in [11]; and weights defined by the client's preferences. In particular, the use of the matrix makes it possible to perform inconsistency improvement, guaranteeing consistent evaluations from a decision-making perspective when the assessment is conducted by experts or by the client using the questionnaire mode.

The collection of the interviews necessary for the construction of the network weights in terms of the frequencies of certain combinations was carried out via any social communication platform. For example, platforms such as Facebook and Instagram were involved, and bots were created on WhatsApp. The authors' aim was in fact to obtain a sample as heterogeneous as possible, capable of expressing all the elasticity provided by the network structure. The individuals, therefore, were not selected according to precise criteria but sought in their fullest diversity. The use of an online platform that allowed all individuals to complete the test using their own devices allowed for effective dissemination that involved many work sectors, many types of study and a wide age range (from 27 to 60). The selection of experts, on the other hand, was carried out according to very specific criteria, defined by a combination of skills and experience. The first criterion considered was education: the experts presented a solid grounding in financial concepts, multi-criteria methodologies, and psychological notions of behavioural finance. Training also includes communication and analytical skills: not only do the experts need to be able to interpret the investor's context and behaviour, but the ability to communicate effectively is also crucial. The second selection criterion is aimed strictly at the scientific field, i.e., research and scientific publications in the context of behavioural finance. Finally, the flexibility and adaptability of the experts were also assessed, as they had to come up with convergent ideas and thoughts by experimental design. The experts involved in the evaluation of the network weights were the same as those who later participated in the discussion of the specific weights in the client's case. The authors considered it crucial to maintain consistency in the decision-making process, particularly since a solid understanding of the network structure used and the definition of its weights could have facilitated more informed judgements.

Table 2. The AHP Fundamental Scale of Saaty in numerical and verbal modes.

The AHP Fundamental Scale	Verbal Mode
1	Equal
2	Equally to Moderately more dominant
3	Moderately more dominant
4	Moderately to Strongly more dominant
5	Strongly more dominant
6	Strongly to Very Strongly more dominant
7	Very Strongly more dominant
8	Very Strongly to Extremely more dominant
9	Extremely more dominant

3. A Case Study

The case study involves the selection of an alternative to realise an investment objective. Two experts and a client are involved in the evaluation.

Objective: To finance an entrepreneurial project by accumulating capital of EUR 50, 000.00 within five years.

The possible alternatives are:

Alternative 1: Medium-Low-Risk Profile Step-by-Step Growth Strategy. The creation of capital for the financing of an entrepreneurial project, with the avoidance of excessive risk. An investment plan is based on a gradual investment in a diversified range of low-risk instruments: allocate 70% in money market funds (low risk) and the remaining 30% in medium-term bonds (medium risk). Present the strategy in a clear and detailed manner, emphasising stability and security. The portfolio is evaluated on a quarterly basis to ensure that the allocation is in line with the objectives, and adjustments are made where necessary.
Alternative 2: Medium-High-Risk Profile-Accelerated Growth Strategy. Rapid accumulation of the necessary capital for the business project while assuming a higher level of risk. The investment plan is based on an aggressive strategy: invest 50% of your assets into stocks (moderate risk), 30% into intermediate-term bonds (moderate risk) and 20% into money market funds (moderate risk). Present the growth-oriented strategy by emphasising the potential for higher returns. Monthly monitoring of the portfolio to react promptly to market fluctuations and adjust in line with performance.

Both options have the same end goal of raising EUR 50, 000.00 to fund an entrepreneurial venture with a different risk profile, investment strategy and monitoring approach. The first option seeks gradual, lower-risk growth, while the second seeks faster, higher-risk growth.

3.1. Questionnaire and Network Structure

The purpose of the application is to verify how, through the client's Kersey score, client risk profile and uncertainty profile, the authors determine the best alternative among a set of alternatives equally satisfying the investment objective, with respect to fixed weights obtained from empirical observations, expert evaluations, and client preferences.

The experimental part thus consists of two phases. The first phase involves the construction of the network and the weights of its elements; the second phase involves the inclusion of the customer's characteristics that determine, in combination with the previous weights, the scale of alternatives.

The implementation of the network does not consider all the clusters discussed in Table 1 but only the clusters relating to uncertainty management, Kersey temperaments and attitude to risk. In this way, the questionnaire submitted to individuals falls within experimental timeframes, which sped up and facilitated the data collection necessary for the construction of certain weights. The ANP built in SuperDecisions is shown in Figure 5.

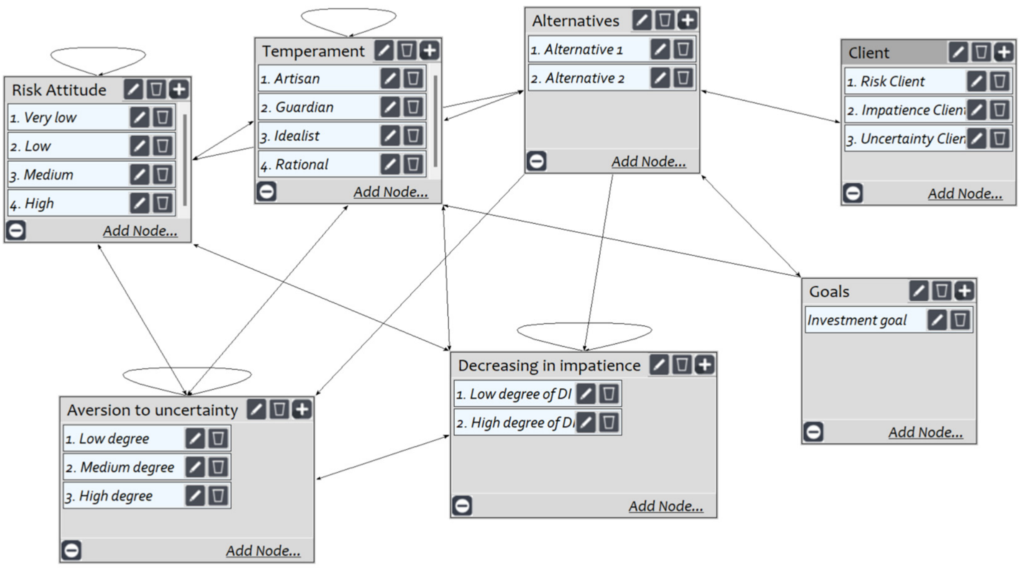

Figure 5. ANP implementation in SuperDecisions.

Obviously, the other clusters, such as socio-demographic characteristics, experience and knowledge, and financial situation can be incorporated into the network by means of a questionnaire that collects the information [11].

The questionnaire consists of 4 sections, with a total of 30 questions: 16 for the calculation of Kersey's temperament, one for the attitude to risk, 2 for the degree of DI, and 12 to derive the degree of time and Aversion to Uncertainty.

3.1.1. Kersey Temperament Sorter

Kersey's temperament questionnaire is set out in Kersey [12] and consists of 16 questions in which 4 alternatives, each corresponding to a specific temperament, must be rated in order of preference. At the end, the main temperament is the one with the lowest score, and everyone is identified by the score quatern of each trait (Idealist score, Rational score, Artisan score, Guardian score).

3.1.2. Attitude to Risk

The question is based on MiFID guidance and aims to understand the types of investments preferred by the individual: "Knowing that the return on an investment is often linked to its exposure to risk, which investment strategy do you prefer?"

Possible answers are: (a) Safety and capital preservation (Potential gains: +5%; Potential losses: −5%). Above all, I want to protect my capital even if this means limiting the return on my investment; (b) Low exposure and limit returns (Potential gains: +10%; Potential losses: −10%). It is OK for my investment to be exposed to slight market fluctuations and in return I derive a modest return; (c) Medium exposure and more attractive returns (Potential gains: +20%; Potential losses: −20%). I am able to expose my investment to larger market fluctuations in order to benefit from larger returns; (d) High exposure and significant growth (Potential gains: +30%; Potential losses: −30%). I want to achieve significant growth, even if I expose my capital to strong market movements.

They outline four profiles: respectively, very-low-risk exposure, low-risk exposure, medium-risk exposure and high-risk exposure.

3.1.3. Decreasing Impatience

To calculate the degree of decrease in impatience [32,33], the hyperbolic factor [33,34] for the indifference pairs $(x, s) \sim (y, t)$ and $(x, s + \sigma) \sim (y, t + \tau)$ where $s < t,\ x < y,\ \tau > 0$ is defined as in Equation (1):

$$H(s, t,\ y, \tau) = \frac{\tau - \sigma}{t\sigma - s\tau} \tag{1}$$

Therefore, the authors determine it for everyone through the following question, fixed $t = 6$, $s = 0$, $\tau = 12$ fixed and $y =$ EUR 500 [18]

"You must receive a sum of y in t months, not before the set date, but, alternatively, there is the possibility to immediately collect a certain result by reducing the total to be collected. How much at least do you want to receive to accept the offer today?"

"You must receive a sum of y in $t + \tau$ months, not before the set date, but you are given the opportunity to anticipate the application and collect a result of x instead of y. To accept the offer, how long do you want to receive the x-digit?"

The set of values obtained breaks down into two almost equal distributions above and below the median value of 0.50. Therefore, there are two classes considered, defined by those whose degree of impatience decreases above the median and below the median. Due to the high variability of the data, the range of which is $(-0.17,\ 59.83)$, this subdivision is best suited to our purposes.

3.1.4. Aversion to Uncertainty

To calculate uncertainty aversion, one must first obtain the distance between the empirical and exponential trends of the individual discount functions. Of this distance over time, the maximum of the absolute values is considered, which indicates the maximum distance between the empirical preferences and those predicted by the DUM [28].

The inconsistency values were clustered through the k-means algorithm, implemented in MATLAB, for a total of $k = 3$ clusters, and the values are shown in Table 3.

Table 3. Classes to define nodes in Decreasing in Impatience cluster.

Low Degree	Medium Degree	High Degree
$(0,\ 0.19)$	$(0.22,\ 0.43)$	$(0.44,\ 0.88)$

The questionnaire was submitted via an online platform and 200 people were interviewed, of whom 47 were excluded because they presented discount function values unsuitable for analysis. Table 4 shows the sample characteristics of the first experimental phase.

Table 4. Characteristics of the sample.

Risk Attitude	Temperament	Aversion to Uncertainty	Decreasing in Impatience
Very Low 27.45%	Artisan 12.42%	Low degree 38.56%	Low degree 50.98%
Low 35.95%	Guardian 5.88%	Medium degree 31.37%	High degree 49.02%
Medium 28.10%	Idealist 36.60%	High degree 30.07%	
High 8.10%	Rational 45.10%		

3.2. Network Weights

Before proceeding to the insertion of the weights, the set of relationships characterising the network can be observed in Tables A1–A7, which shows the unweighted supermatrix of the network, divided into seven parts to improve readability and listed in Appendix A to avoid confusion in the layout. By default, without the insertion of weights, the unmatched parts have essentially equal weights. It is possible to observe:

- The clusters Risk Attitude, Temperament, Aversion to Uncertainty, and Decreasing in Impatience are characterised by dependencies and interdependencies;
- Alternatives are evaluated with respect to how closely they match Temperaments, Risk Attitude, investment objectives, and customer characteristics (temperament, risk, impatience and uncertainty);
- The investment objective is only related to temperaments. In this way, assuming that both alternatives satisfy the objective in the same way and once all network weights have been defined, the definition of the best alternative for the individual customer will be determined by the individual temperament weights.

By following the procedure indicated in [11], through the experts' evaluation and the client's preferences, the researchers proceed with the insertion of weights expressing interdependence between nodes and interdependence of the same cluster.

It is important to note that the direct inclusion of the weight of dependencies between the nodes of different clusters in terms of the frequency of the corresponding relationship within the distribution may depend on the characteristics of the population under consideration. To overcome this problem, the inclusion of the weights of interdependencies between nodes of the same cluster is an essential step when considering within the network the characteristics of the sample on which the weights are being constructed. From a decision-making point of view, this is equivalent to weighing the weights of interdependencies between nodes in different clusters against the influence of nodes in the same cluster. To better explain this concept, consider the Temperament and Risk Attitude clusters. The weight of the Artisan with respect to the attitude to risk is defined by how many Artisans fall into a profile of Very low, Low, Medium, and High risk, respectively. This weight does not depend on the quantity of Artisans but only on the frequency of correspondences (Artisan, Very low risk), (Artisan, Low risk), (Artisan, Medium risk), (Artisan, High risk). The opposite, i.e., the weight of the very-low-risk profile with respect to the Temperament cluster, expresses the frequency of correspondences (Artisan, Very low risk), (Rational, Very low risk), (Idealist, Very low risk), (Guardian, Very low risk). In this case, this frequency is influenced by the way in which the four profiles are distributed throughout the sample. So, it is necessary to weigh the Artisan temperament against the other temperaments: the Artisan against the Artisan has weight 1, and against the Rational it has weight $(number\ of\ Artisans)/(number\ of\ Rationales)$, and so on... In this way, if the Artisans are greater in number than the Rationales, the less-populated temperament is given enough weight to compensate for its lesser influence. These ratios, whether greater or less than 1, are converted into numbers between 0 and 1 and represent the weights between nodes in the same cluster. This allows the influence of specific sample characteristics to be dampened.

The weight of the Risk Attitude cluster with respect to the nodes Alternative 1 and Alternative 2 is defined by experts' judgement. Table 5 shows the experts' discussions with respect to the two alternatives and the four Risk Attitude nodes.

The weights of the alternatives with respect to the four temperaments were evaluated by the experts according to the characteristics shown in Table 6.

Table 5. Expert discussions regarding the two alternatives and four Risk Attitude nodes.

Risk Profile	Alternative 1	Alternative 2
Very low risk	Well-aligned with a very-low-risk profile: allocations to money market funds and intermediate-term bonds are geared towards lower-risk assets, offering stability and capital preservation.	High exposure to equity and medium-term bonds may be too exposed to market volatility for risk-averse investors.
Low risk	Well aligned with a low-risk profile: allocating to low and intermediate risk instruments is consistent with keeping risk low and protecting capital.	A low-risk profile responds poorly to this alternative: the equity allocation is riskier than a risk-averse investor would like to take.
Medium risk	This alternative may be too conservative: if the investor is willing to take a moderate level of risk, she may wish to seek greater opportunities for growth through a more balanced mix of medium-risk and higher-risk assets.	For those willing to take a moderate level of risk for better returns, the allocation between equities, bonds and low-risk instruments could be satisfactory.
High risk	For a high-risk profile, this alternative does not respond optimally: for those willing to take on more risk for potentially higher returns, the predominant allocation to low- and medium-risk assets may not be aggressive enough.	This alternative could also correspond to a high-risk profile even if it is more suitable for a medium-high-risk profile.

Table 6. Some characteristics of the four temperaments considered to assess the fit of the alternatives.

Temperaments	Characteristics
Rational	The Rational has a good risk tolerance and is the profile closest to that idealised by classical finance.
Idealist	The Idealist has a moderate appetite for risk. This propensity is more likely to depend on the nature of the investment than on the potential for a return.
Artisan	The Artisan likes risk and high returns in a short period of time. Losses are well taken.
Guardian	The Guardian tends to stay in his comfort zone and is generally risk-averse and conservative. Investing is a way of protecting capital. Therefore, they prefer to sacrifice some of what they want to earn rather than take risks.

3.3. Input of Weights and Synthesis of Alternatives

As discussed before, for the hypothesis, the researchers assumed that the alternatives meet the investment objective with equal weight. Starting with the Alternatives nodes, compared to the assessments discussed in the previous section, weights were associated to define how well the two alternatives adhere to the risk profiles and the four temperaments. The experts therefore completed the questionnaire to compare Alternative 1 and Alternative 2 against the Temperament, Risk Attitude, Aversion to Uncertainty and Decreasing in Impatience clusters. Using the matrix mode, the weights were adjusted to obtain the lowest inconsistency index to make the judgements as consistent as possible. The result of their evaluations is expressed through Tables A8–A14 in Appendix A, which shows the unweighted supermatrix of the network after the weights have been entered.

Client preferences relate to the importance of clusters. It is explained to the customer that the final ranking depends on what one prefers to have importance among the network elements. The ratings were entered through the questionnaire mode combined with the matrix mode to correct for inconsistency values.

The weights that do not depend on the sample distribution allow for important observations that contributed to the experts' assessment.

3.3.1. Temperament Node

With respect to the temperament of the Artisans, it is found that slightly more than 50% are distributed among a medium-high-risk profile, in line with the profile characteristics. The degree of uncertainty aversion is mostly low, and the degree of DI is low. The Guardians are distinguished by the smallest percentage of individuals in the high-risk class (0.001%): most are distributed between very low and low risk. The degree of uncertainty aversion is high (55.55%), while the degree of DI is low. Idealists are distributed on a low- to medium-risk profile, with a low to medium degree of uncertainty aversion and a low degree of DI. Rationales also have a low- to medium-risk profile, but, unlike Idealists, there is a greater distribution in the high-risk profile than the very-low-risk profile. Rationales also differ in that they have a low inconsistency, but, unlike Artisans, they have a high degree of DI.

3.3.2. Risk Attitude Node

Individuals with a very-low-risk profile have a low average degree of uncertainty aversion and a mostly high degree of impatience decrease. In contrast to the very-low-risk profile, individuals with a low-risk profile have a high degree of uncertainty aversion and a low degree of DI. The medium-risk profile stands out in that it has the highest distribution for a high degree of DI, while with respect to uncertainty aversion it has a distribution towards a medium-low profile. The high-risk profile has the highest distribution for a low degree of inconsistency and the highest distribution for a low degree of DI.

3.3.3. Aversion to Uncertainty Node and DI Node

A low degree of uncertainty aversion mostly corresponds to a low-medium-risk profile and a low degree of DI, for which it has the highest distribution (57.62%). Individuals with a medium degree of uncertainty aversion are evenly distributed over the very low, low, and medium risk classes and have a very low distribution for the high-risk profile. With respect to the degree of DI, however, a high degree prevails. Finally, the high uncertainty aversion class is evenly distributed with respect to the degree of DI, with a low-risk profile. A low degree of DI is distributed more in the middle class of uncertainty aversion and medium-risk profile. Individuals with a low degree of DI, on the other hand, correspond to a mostly low degree of uncertainty aversion and a low-risk profile.

3.3.4. Client Characteristics

The final ranking involves the experts' input and an evaluation of the customer's characteristics. Thus, the experts evaluate the nodes in the Client cluster against the nodes in the Alternatives cluster and vice versa. This step is key for strategic customisation as it relates the customer classes to the characteristics of the alternatives. In particular, the Client is identified by a medium-risk profile, a low degree of uncertainty aversion and a low degree of DI. Finally, the Kersey test score is entered to determine the weights of the nodes in the Temperaments cluster with respect to the Goals cluster. Table 7 shows the influence of the four temperaments for the client in question.

Table 7. Kersey's test results for the client.

Temperament	Score
Artisan	0.28
Guardian	0.25
Idealist	0.23
Rational	0.24

3.3.5. Final Ranking

The inclusion of the weights discussed generates a ranking of the alternatives, represented in Table 8. Tables A8–A21 in Appendix A are the unweighted and weighted supermatrix of the final network, respectively.

Table 8. Synthesis of alternatives.

Alternatives	Score
Alternative 1	0.33
Alternative 2	0.67

4. Discussion

The present paper discussed the implementation of an ANP to support financial decision-making in the context of behavioural finance. The affirmation of behavioural finance and interventions aimed at customer protection and profiling make the selection of an investment strategy an even more complex process. Indeed, besides having to consider the financial variables that characterise the decision-making context, it is important to assess the characteristics of the individual for an efficient advisory service. In fact, a key aspect of recent regulatory requirements to improve intermediaries' knowledge of their clients is the concept of client profiling. The aim is to ensure that services and products are personalised. The profiling process is therefore complex and full of interrelated variables that influence each other. In particular, the creation of client profiles involves transforming the information collected into an appropriate form for extracting knowledge. Once the initial questions are completed, a financial advisor will be able to determine the type of investment to recommend to the client by compiling a "risk profile" based on the information collected. Obtaining a profile requires organising the information collected, including selecting relevant information, excluding redundant information, and combining related information [46].

The work presented has several original and useful aspects to support the process of profiling and selecting customised alternatives. The methodology is based on the extension of a previously used hierarchical approach [11,29,40,47]. In previous work, the hierarchical structure made it possible to extrapolate information that helped to successfully enrich the relationships between individual characteristics. The need to include more criteria for profiling and the intention to support a more complex decision-making context motivated the extension from the AHP to the ANP. The structure of the network, discussed in Section 2, allows for the inclusion of all the indications obtained by combining the literature and the framework presented in Table 1 [4]. The proposed approach contributes several original elements to the existing literature. The first element refers to Pompian's behavioural finance work [8,48], which, with accurate descriptions, defines customised approaches for different types of investors. In this context, the ANP would allow for an extension, deepening and simplification of the profiling process, in which expert judgements are crucial for the synthesis of results. The greater accuracy of the assessments is linked in particular to the possibility of being able to include dependencies and interdependencies while simultaneously considering the individual in all its many nuances. To emphasise the importance of this aspect, it was analysed in [29] how individuals with the same dominant temperament as Kersey may take different attitudes to the second dominant trait. The second element that characterises the originality of this work is the inclusion of measures related to the context of uncertainty, which is treated separately from risk. In this respect, intertemporal choice theory provides measures of behavioural and cognitive attitudes. In fact, recent studies [28,47] on the evolution of the discount function show how to quantify the relationship between uncertainty and decision-making under conditions of uncertainty. The measures used in this paper relate to two fundamental elements of the decision-making process: cognitive biases and subjective perception of time. The former is measured in terms of decreasing impatience and the latter in terms of uncertainty aversion.

The implementation of a case study involves only a part of the network proposed in Figure 4, which was reduced for experiment structural reasons. The development of the empirical part allows considerable considerations to be made that confirm the efficiency of the methodology used. First of all, through the inclusion of weights, interesting relationships emerged between the Risk Attitude clusters, uncertainty measures and temperaments, discussed in Section 3.3. Furthermore, although the alternatives are defined with the same weight with respect to the investment objective, they were distributed with a weight that corresponds to the client's behavioural characteristics. However, a priori it would not have been possible to easily determine which alternative was better. In fact, the client presents the Artisan as the first trait and the Guardian as the second trait—temperaments with very different financial attitudes. Similarly, the client has a medium-risk profile and a low DI—a rare combination, as discussed in Section 3.3.2. When filling in the weights, it was possible to highlight the role of experts in the evaluation, as discussed in Tables 5 and 6. However, the authors point out that the customer plays a central role in the synthesis of results—a key concept for effective strategic customisation. Customer centrality is composed of preferences and characteristics. With respect to preferences, the customer is called upon to discuss the importance of clusters, having the role of the only effective decision-maker regarding the problem. The characteristics, on the other hand, collected in the Client and Temperaments clusters, distinguish the specific case and specify the importance of the client as a set of nodes. For example, from the weights generated by the expert evaluation for the Alternatives and Client clusters, Alternative 2 might be more suitable with respect to the Risk node (medium) but less suitable with respect to the DI degree (low). The possibility of being able to aggregate all these possible combinations underlines the effectiveness and flexibility of the discussed method.

Possible future studies involve the inclusion of more elements in the network, through the creation of sub-networks to further decompose customer and decision context characteristics. Again, by increasing the interviews used for frequency analysis, it may be possible to obtain even more precise weights, increasing the efficiency of the process. Furthermore, given the central role of expert evaluation, the number of experts involved could be expanded by structuring their judgements as a group decision problem. This paper combines regulatory guidance and qualitative and quantitative findings from the literature in order to support financial decision-making in the context of behavioural finance.

5. Conclusions

The objective of this study was to provide a methodology that could support the financial decision-making process in the context of behavioural finance. The complexity of the context in which financial decisions are made and the need to include investor-specific characteristics in the assessment in order to offer the best choice support service were the main motivations for this study. Indeed, the criteria to be considered and all the possible connections and interconnections are unmanageable without an appropriate decision support structure. The objectives mentioned in the introduction, and briefly recalled here, were achieved by the study in a clear and effective manner. The main findings address both the methodological and conceptual aspects of the research presented.

With respect to the methodological aspect, the authors proved how a network structure can be capable of encompassing all possible interactions between the fundamental elements of profiling, both those indicated by the regulatory framework and those indicated in the literature (cited in Table 1), and the elements that behavioural finance emphasises. In particular, the implementation of the network allowed the authors to define the best alternative that includes all the nuances that characterise the customer. A fundamental element of the methodological aspect is the inclusion of preferences on the part of the customer, i.e., the personal involvement that fosters a more serene acceptance of the alternative: the customer is no longer merely a passive part of the decision-making context but becomes an active component that significantly influences the choice.

With respect to the conceptual aspect, on the other hand, research has confirmed that the individual has to be evaluated in all their nuances, especially when placed in relation to the context of risk and uncertainty. From a behavioural point of view, the distinction between risk and uncertainty can be a pivotal point for defining more informed strategies. Indeed, the various observations made in Section 3.3 provide empirical evidence that attitudes towards risk and uncertainty do not always coincide.

Thus, in conclusion, the authors can state that the research received a double confirmation from both a methodological and conceptual point of view. The methodology used proved to be effective and allowed the client to be an active participant in the decision-making process, while at the same time maintaining partial protection against possible cognitive errors thanks to the network and expert input. This aspect is of crucial importance as it emphasises the central role of the customer and his preferences, thus contributing to the creation of informed, structured, and customised solutions. The second crucial aspect concerns the conceptual nature of the main research findings, highlighting the importance of nuances, i.e., the different combinations that make each individual unique. This emphasises the need to consider the behavioural aspect in investment plan evaluations, especially when the decision-making environment is characterised by uncertainty and risk. As we discussed in Section 3.3 and as mentioned earlier, risk and uncertainty preferences do not always coincide, but the flexibility of the network structure allows such combinations to be considered.

With respect to the ranking of alternatives, although the ANP was nevertheless effective, there is an inherent limitation of the methodology. In particular, although it is a powerful tool for tackling complex and diverse decision-making problems, its output depends on human subjectivity in evaluating the criteria and the relationships between them. Combining the ANP with other multi-criteria methods may increase the effectiveness of the method and may help to mitigate this limitation. In this context, artificial neural networks (ANNs) [49–51] can make a strong contribution to research. Some advantages of combining ANNs and ANPs concern, for instance, the integration of quantitative data and qualitative knowledge. Indeed, ANNs are effective in handling large amounts of data and ANPs are essential for the inclusion of subjective judgement, which is indispensable in the context of behavioural finance. In this way, a deeper insight into the decision-making context can be obtained. Furthermore, the combination of the two instruments can contribute to the understanding of structure behaviour. Indeed, ANNs may reveal important relationships between data that, combined with expert judgement, may offer a much richer perspective of network inter-connections and intra-connections.

A further way to reduce the impact of the limitations of the ANP associated with subjective judgement in implementation is to include more experts in the decision-making context [52].

However, with respect to the management of uncertainty, decision-makers have a limited capacity that depends not only on cognitive limitations but also on modelling limitations. The uncertain context, in fact, refers to the lack of complete information with respect to future events that do not allow for the formalisation of models. In this context, fuzzy logic is suitable for overcoming these restrictions [53,54]. Recently, in the literature, Fourier-based type-2 fuzzy neural networks have been used to address the modelling of uncertainty by combining fuzzy logic with the Fourier transform [55,56]. While the latter is particularly functional in handling fuzzy and uncertain information, it does not contain the behavioural part, and the interpretation of results may not be practical. The fusion of the ANP with Fourier-based type-2 fuzzy neural networks could create increasingly complete and robust models. In conclusion, it could be advantageous to combine expert evaluation with the mentioned methodologies.

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Appendix A

Table A1. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Alternatives cluster.

		Alternatives	
		1. Alternative 1	**2. Alternative 2**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.3333	0.3333
	2. Medium degree	0.3333	0.3333
	3. High degree	0.3333	0.3333
Client	1. Risk Client	0.3333	0.3333
	2. Impatience Client	0.3333	0.3333
	3. Uncertainty Client	0.3333	0.3333
Decreasing in Impatience	1. Low degree of DI	0.5000	0.5000
	2. High degree of DI	0.5000	0.5000
Goals	Investment goal	1.0000	1.0000
Risk Attitude	1. Very low	0.2500	0.2500
	2. Low	0.2500	0.2500
	3. Medium	0.2500	0.2500
	4. High	0.2500	0.2500
Temperament	1. Artisan	0.2500	0.2500
	2. Guardian	0.2500	0.2500
	3. Idealist	0.2500	0.2500
	4. Rational	0.2500	0.2500

Table A2. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Aversion to Uncertainty cluster.

		Aversion to Uncertainty		
		1. Low Degree	**2. Medium Degree**	**3. High Degree**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.3333	0.3333	0.3333
	2. Medium degree	0.3333	0.3333	0.3333
	3. High degree	0.3333	0.3333	0.3333
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.5000	0.5000	0.5000
	2. High degree of DI	0.5000	0.5000	0.5000
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.2500	0.2500	0.2500
	2. Low	0.2500	0.2500	0.2500
	3. Medium	0.2500	0.2500	0.2500
	4. High	0.2500	0.2500	0.2500
Temperament	1. Artisan	0.2500	0.2500	0.2500
	2. Guardian	0.2500	0.2500	0.2500
	3. Idealist	0.2500	0.2500	0.2500
	4. Rational	0.2500	0.2500	0.2500

Table A3. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Client cluster.

		Client		
		1. Risk Client	**2. Impatience Client**	**3. Uncertainty Client**
Alternatives	1. Alternative 1	0.5000	0.5000	0.5000
	2. Alternative 2	0.5000	0.5000	0.5000
Aversion to Uncertainty	1. Low degree	0.0000	0.0000	0.0000
	2. Medium degree	0.0000	0.0000	0.0000
	3. High degree	0.0000	0.0000	0.0000
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.0000	0.0000	0.0000
	2. High degree of DI	0.0000	0.0000	0.0000
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0000	0.0000	0.0000
	2. Low	0.0000	0.0000	0.0000
	3. Medium	0.0000	0.0000	0.0000
	4. High	0.0000	0.0000	0.0000
Temperament	1. Artisan	0.0000	0.0000	0.0000
	2. Guardian	0.0000	0.0000	0.0000
	3. Idealist	0.0000	0.0000	0.0000
	4. Rational	0.0000	0.0000	0.0000

Table A4. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Decreasing in Impatience cluster.

		Decreasing in Impatience	
		1. Low Degree of DI	**2. High Degree of DI**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.3333	0.3333
	2. Medium degree	0.3333	0.3333
	3. High degree	0.3333	0.3333
Client	1. Risk Client	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.5000	0.5000
	2. High degree of DI	0.5000	0.5000
Goals	Investment goal	0.0000	0.0000
Risk Attitude	1. Very low	0.2500	0.2500
	2. Low	0.2500	0.2500
	3. Medium	0.2500	0.2500
	4. High	0.2500	0.2500
Temperament	1. Artisan	0.2500	0.2500
	2. Guardian	0.2500	0.2500
	3. Idealist	0.2500	0.2500
	4. Rational	0.2500	0.2500

Table A5. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Goals cluster.

		Goals
		Investment Goal
Alternatives	1. Alternative 1	0.5000
	2. Alternative 2	0.5000
Aversion to Uncertainty	1. Low degree	0.0000
	2. Medium degree	0.0000
	3. High degree	0.0000
Client	1. Risk Client	0.0000
	2. Impatience Client	0.0000
	3. Uncertainty Client	0.0000
Decreasing in Impatience	1. Low degree of DI	0.0000
	2. High degree of DI	0.0000
Goals	Investment goal	0.0000
Risk Attitude	1. Very low	0.0000
	2. Low	0.0000
	3. Medium	0.0000
	4. High	0.0000
Temperament	1. Artisan	0.2500
	2. Guardian	0.2500
	3. Idealist	0.2500
	4. Rational	0.2500

Table A6. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Risk Attitude cluster.

		Risk Attitude			
		1. Very low	**2. Low**	**3. Medium**	**4. High**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.3333	0.3333	0.3333	0.3333
	2. Medium degree	0.3333	0.3333	0.3333	0.3333
	3. High degree	0.3333	0.3333	0.3333	0.3333
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.5000	0.5000	0.5000	0.5000
	2. High degree of DI	0.5000	0.5000	0.5000	0.5000
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.2500	0.2500	0.2500	0.2500
	2. Low	0.2500	0.2500	0.2500	0.2500
	3. Medium	0.2500	0.2500	0.2500	0.2500
	4. High	0.2500	0.2500	0.2500	0.2500
Temperament	1. Artisan	0.2500	0.2500	0.2500	0.2500
	2. Guardian	0.2500	0.2500	0.2500	0.2500
	3. Idealist	0.2500	0.2500	0.2500	0.2500
	4. Rational	0.2500	0.2500	0.2500	0.2500

Table A7. Unweighted supermatrix after developing the relationships characterising the network. Exporting output data from the SuperDecisions software: weights against the Temperament cluster.

		Temperament			
		1. Artisan	**2. Guardian**	**3. Idealist**	**4. Rational**
Alternatives	1. Alternative 1	0.5000	0.5000	0.5000	0.5000
	2. Alternative 2	0.5000	0.5000	0.5000	0.5000
Aversion to Uncertainty	1. Low degree	0.3333	0.3333	0.3333	0.3333
	2. Medium degree	0.3333	0.3333	0.3333	0.3333
	3. High degree	0.3333	0.3333	0.3333	0.3333
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.5000	0.5000	0.5000	0.5000
	2. High degree of DI	0.5000	0.5000	0.5000	0.5000
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.2500	0.2500	0.2500	0.2500
	2. Low	0.2500	0.2500	0.2500	0.2500
	3. Medium	0.2500	0.2500	0.2500	0.2500
	4. High	0.2500	0.2500	0.2500	0.2500
Temperament	1. Artisan	0.2500	0.2500	0.2500	0.2500
	2. Guardian	0.2500	0.2500	0.2500	0.2500
	3. Idealist	0.2500	0.2500	0.2500	0.2500
	4. Rational	0.2500	0.2500	0.2500	0.2500

Table A8. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Alternatives cluster.

		Alternatives	
		1. Alternative 1	**2. Alternative 2**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.7096	0.0924
	2. Medium degree	0.1354	0.4844
	3. High degree	0.1550	0.4232
Client	1. Risk Client	0.3196	0.1248
	2. Impatience Client	0.5584	0.7248
	3. Uncertainty Client	0.1220	0.1504
Decreasing in Impatience	1. Low degree of DI	0.8571	0.2000
	2. High degree of DI	0.1429	0.8000
Goals	Investment goal	1.0000	1.0000
Risk Attitude	1. Very low	0.4322	0.0531
	2. Low	0.4322	0.0966
	3. Medium	0.0888	0.3206
	4. High	0.0468	0.5297
Temperament	1. Artisan	0.0696	0.5069
	2. Guardian	0.6567	0.0480
	3. Idealist	0.1437	0.2331
	4. Rational	0.1300	0.2121

Table A9. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Aversion to Uncertainty cluster.

		Aversion to Uncertainty		
		1. Low Degree	**2. Medium Degree**	**3. High Degree**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.2857	0.2842	0.2847
	2. Medium degree	0.3486	0.3509	0.3504
	3. High degree	0.3657	0.3649	0.3650
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.5763	0.4375	0.5000
	2. High degree of DI	0.4237	0.5625	0.5000
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.2882	0.3333	0.1957
	2. Low	0.2712	0.3333	0.4999
	3. Medium	0.2882	0.3333	0.2174
	4. High	0.1525	0.0001	0.0870
Temperament	1. Artisan	0.1356	0.1458	0.0870
	2. Guardian	0.0339	0.0417	0.1087
	3. Idealist	0.3559	0.4169	0.3261
	4. Rational	0.4746	0.3957	0.4782

Table A10. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Client cluster.

		Client		
		1. Risk Client	**2. Impatience Client**	**3. Uncertainty Client**
Alternatives	1. Alternative 1	0.1429	0.2000	0.1250
	2. Alternative 2	0.8571	0.8000	0.8750
Aversion to Uncertainty	1. Low degree	0.0000	0.0000	0.0000
	2. Medium degree	0.0000	0.0000	0.0000
	3. High degree	0.0000	0.0000	0.0000
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.0000	0.0000	0.0000
	2. High degree of DI	0.0000	0.0000	0.0000
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0000	0.0000	0.0000
	2. Low	0.0000	0.0000	0.0000
	3. Medium	0.0000	0.0000	0.0000
	4. High	0.0000	0.0000	0.0000
Temperament	1. Artisan	0.0000	0.0000	0.0000
	2. Guardian	0.0000	0.0000	0.0000
	3. Idealist	0.0000	0.0000	0.0000
	4. Rational	0.0000	0.0000	0.0000

Table A11. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Decreasing in Impatience cluster.

		Decreasing in Impatience	
		1. Low Degree of DI	**2. High Degree of DI**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.4359	0.3333
	2. Medium degree	0.2692	0.3600
	3. High degree	0.2949	0.3067
Client	1. Risk Client	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.4902	0.3333
	2. High degree of DI	0.5098	0.6667
Goals	Investment goal	0.0000	0.0000
Risk Attitude	1. Very low	0.2436	0.3067
	2. Low	0.4102	0.3067
	3. Medium	0.2436	0.3200
	4. High	0.1026	0.0667
Temperament	1. Artisan	0.1667	0.0800
	2. Guardian	0.0641	0.0533
	3. Idealist	0.4103	0.3200
	4. Rational	0.3590	0.5467

Table A12. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Goals cluster.

		Goals
		Investment Goal
Alternatives	1. Alternative 1	0.50000
	2. Alternative 2	0.50000
Aversion to Uncertainty	1. Low degree	0.00000
	2. Medium degree	0.00000
	3. High degree	0.00000
Client	1. Risk Client	0.00000
	2. Impatience Client	0.00000
	3. Uncertainty Client	0.00000
Decreasing in Impatience	1. Low degree of DI	0.00000
	2. High degree of DI	0.00000
Goals	Investment goal	0.00000
Risk Attitude	1. Very low	0.00000
	2. Low	0.00000
	3. Medium	0.00000
	4. High	0.00000
Temperament	1. Artisan	0.27630
	2. Guardian	0.25504
	3. Idealist	0.22606
	4. Rational	0.24260

Table A13. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Risk Attitude cluster.

		Risk Attitude			
		1. Very Low	**2. Low**	**3. Medium**	**4. High**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.4048	0.2909	0.3953	0.6923
	2. Medium degree	0.3809	0.2909	0.3721	0.0001
	3. High degree	0.2143	0.4182	0.2326	0.3076
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.4523	0.5818	0.4419	0.6154
	2. High degree of DI	0.5477	0.4182	0.5581	0.3846
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.1675	0.1675	0.1669	0.1676
	2. Low	0.1273	0.1279	0.1277	0.1297
	3. Medium	0.1642	0.1637	0.1637	0.1622
	4. High	0.5410	0.5409	0.5417	0.5405
Temperament	1. Artisan	0.1190	0.0726	0.1395	0.3077
	2. Guardian	0.0476	0.0726	0.0698	0.0001
	3. Idealist	0.4047	0.3825	0.3488	0.2308
	4. Rational	0.4286	0.4723	0.4418	0.4613

Table A14. Unweighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Temperament cluster.

		Temperament			
		1. Artisan	**2. Guardian**	**3. Idealist**	**4. Rational**
Alternatives	1. Alternative 1	0.1111	0.8889	0.7500	0.2500
	2. Alternative 2	0.8889	0.1111	0.2500	0.7500
Aversion to Uncertainty	1. Low degree	0.4211	0.4963	0.3750	0.4058
	2. Medium degree	0.3684	0.4963	0.3571	0.2754
	3. High degree	0.2105	0.0074	0.2679	0.3188
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.6842	0.5556	0.4285	0.5942
	2. High degree of DI	0.3158	0.4444	0.5715	0.4058
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.2632	0.2222	0.3036	0.2609
	2. Low	0.2105	0.4444	0.3750	0.3768
	3. Medium	0.3158	0.3333	0.2679	0.2754
	4. High	0.2105	0.0001	0.0536	0.0870
Temperament	1. Artisan	0.1032	0.2670	0.2687	0.0346
	2. Guardian	0.2178	0.5682	0.5665	0.8301
	3. Idealist	0.3044	0.0909	0.0911	0.0271
	4. Rational	0.3746	0.0739	0.0738	0.1082

Table A15. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Alternatives cluster.

		Alternatives	
		1. Alternative 1	**2. Alternative 2**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.1106	0.0144
	2. Medium degree	0.0211	0.0755
	3. High degree	0.0242	0.0660
Client	1. Risk Client	0.1544	0.0603
	2. Impatience Client	0.2698	0.3502
	3. Uncertainty Client	0.0589	0.0727
Decreasing in Impatience	1. Low degree of DI	0.0772	0.0180
	2. High degree of DI	0.0129	0.0721
Goals	Investment goal	0.0696	0.0696
Risk Attitude	1. Very low	0.0176	0.0022
	2. Low	0.0176	0.0039
	3. Medium	0.0036	0.0131
	4. High	0.0019	0.0216
Temperament	1. Artisan	0.0112	0.0813
	2. Guardian	0.1054	0.0077
	3. Idealist	0.0230	0.0374
	4. Rational	0.0209	0.0340

Table A16. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Aversion to Uncertainty cluster.

		Aversion to Uncertainty		
		1. Low Degree	**2. Medium Degree**	**3. High Degree**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.0936	0.0931	0.0933
	2. Medium degree	0.1142	0.1149	0.1148
	3. High degree	0.1198	0.1195	0.1196
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.1317	0.1000	0.1142
	2. High degree of DI	0.0968	0.1285	0.1142
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0927	0.1072	0.0630
	2. Low	0.0872	0.1072	0.1609
	3. Medium	0.0927	0.1072	0.0699
	4. High	0.0491	0.0000	0.0280
Temperament	1. Artisan	0.0166	0.0178	0.0106
	2. Guardian	0.0041	0.0051	0.0133
	3. Idealist	0.0435	0.0509	0.0398
	4. Rational	0.0580	0.0483	0.0584

Table A17. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Client cluster.

		Client		
		1. Risk Client	**2. Impatience Client**	**3. Uncertainty Client**
Alternatives	1. Alternative 1	0.1429	0.2000	0.1250
	2. Alternative 2	0.8571	0.8000	0.8750
Aversion to Uncertainty	1. Low degree	0.0000	0.0000	0.0000
	2. Medium degree	0.0000	0.0000	0.0000
	3. High degree	0.0000	0.0000	0.0000
Client	1. Risk Client	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.0000	0.0000	0.0000
	2. High degree of DI	0.0000	0.0000	0.0000
Goals	Investment goal	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0000	0.0000	0.0000
	2. Low	0.0000	0.0000	0.0000
	3. Medium	0.0000	0.0000	0.0000
	4. High	0.0000	0.0000	0.0000
Temperament	1. Artisan	0.0000	0.0000	0.0000
	2. Guardian	0.0000	0.0000	0.0000
	3. Idealist	0.0000	0.0000	0.0000
	4. Rational	0.0000	0.0000	0.0000

Table A18. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Decreasing in Impatience cluster.

		Decreasing in Impatience	
		1. Low Degree of DI	**2. High Degree of DI**
Alternatives	1. Alternative 1	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.0810	0.0620
	2. Medium degree	0.0500	0.0669
	3. High degree	0.0548	0.0570
Client	1. Risk Client	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.1402	0.0953
	2. High degree of DI	0.1458	0.1907
Goals	Investment goal	0.0000	0.0000
Risk Attitude	1. Very low	0.0438	0.0552
	2. Low	0.0738	0.0552
	3. Medium	0.0438	0.0575
	4. High	0.0185	0.0120
Temperament	1. Artisan	0.0580	0.0279
	2. Guardian	0.0223	0.0186
	3. Idealist	0.1429	0.1114
	4. Rational	0.1250	0.1904

Table A19. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Goals cluster.

		Goals
		Investment Goal
Alternatives	1. Alternative 1	0.3333
	2. Alternative 2	0.3333
Aversion to Uncertainty	1. Low degree	0.0000
	2. Medium degree	0.0000
	3. High degree	0.0000
Client	1. Risk Client	0.0000
	2. Impatience Client	0.0000
	3. Uncertainty Client	0.0000
Decreasing in Impatience	1. Low degree of DI	0.0000
	2. High degree of DI	0.0000
Goals	Investment goal	0.0000
Risk Attitude	1. Very low	0.0000
	2. Low	0.0000
	3. Medium	0.0000
	4. High	0.0000
Temperament	1. Artisan	0.0921
	2. Guardian	0.0850
	3. Idealist	0.0754
	4. Rational	0.0809

Table A20. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Risk Attitude cluster.

		Risk Attitude			
		1. Very Low	**2. Low**	**3. Medium**	**4. High**
Alternatives	1. Alternative 1	0.0000	0.0000	0.0000	0.0000
	2. Alternative 2	0.0000	0.0000	0.0000	0.0000
Aversion to Uncertainty	1. Low degree	0.0459	0.0330	0.0448	0.0785
	2. Medium degree	0.0432	0.0330	0.0422	0.0000
	3. High degree	0.0243	0.0474	0.0264	0.0349
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.1101	0.1416	0.1076	0.1498
	2. High degree of DI	0.1333	0.1018	0.1358	0.0936
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0144	0.0144	0.0143	0.0144
	2. Low	0.0109	0.0110	0.0110	0.0111
	3. Medium	0.0141	0.0141	0.0141	0.0139
	4. High	0.0465	0.0465	0.0465	0.0464
Temperament	1. Artisan	0.0663	0.0405	0.0778	0.1715
	2. Guardian	0.0265	0.0405	0.0389	0.0001
	3. Idealist	0.2256	0.2132	0.1944	0.1287
	4. Rational	0.2389	0.2632	0.2463	0.2571

Table A21. Weighted supermatrix after the inclusion of the weights. Exporting output data from the SuperDecisions software: weights against the Temperament cluster.

		Temperament			
		1. Artisan	**2. Guardian**	**3. Idealist**	**4. Rational**
Alternatives	1. Alternative 1	0.0565	0.4522	0.3815	0.1272
	2. Alternative 2	0.4522	0.0565	0.1272	0.3815
Aversion to Uncertainty	1. Low degree	0.0746	0.0880	0.0665	0.0719
	2. Medium degree	0.0653	0.0880	0.0633	0.0488
	3. High degree	0.0373	0.0013	0.0475	0.0565
Client	1. Risk Client	0.0000	0.0000	0.0000	0.0000
	2. Impatience Client	0.0000	0.0000	0.0000	0.0000
	3. Uncertainty Client	0.0000	0.0000	0.0000	0.0000
Decreasing in Impatience	1. Low degree of DI	0.1122	0.0911	0.0703	0.0974
	2. High degree of DI	0.0518	0.0729	0.0937	0.0665
Goals	Investment goal	0.0000	0.0000	0.0000	0.0000
Risk Attitude	1. Very low	0.0187	0.0158	0.0215	0.0185
	2. Low	0.0149	0.0315	0.0266	0.0267
	3. Medium	0.0224	0.0236	0.0190	0.0195
	4. High	0.0149	0.0000	0.0038	0.0062
Temperament	1. Artisan	0.0082	0.0211	0.0213	0.0027
	2. Guardian	0.0172	0.0450	0.0448	0.0657
	3. Idealist	0.0241	0.0072	0.0072	0.0021
	4. Rational	0.0297	0.0058	0.0058	0.0086

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