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Review

Profiling Decision-Making Styles Under Healthcare Resource Scarcity: An Interdisciplinary Clustering Approach

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Abstract

Scarcity of healthcare resources requires prioritisation decisions that raise complex ethical, economic, and social challenges. While normative frameworks provide guidance on how such decisions ought to be made, growing evidence suggests that individuals differ substantially in how they approach morally charged allocation choices. This study investigates heterogeneity in decision-making styles and support for healthcare prioritisation criteria using an interdisciplinary approach that integrates health economics, social psychology, and computational methods to identify latent decision-making profiles among a sample of adults residing in Portugal. Data were collected from adults residing in Portugal using a structured online questionnaire comprising socio-demographic characteristics, decision-making styles, and preferences elicited through twenty hypothetical healthcare rationing scenarios. The results reveal three meaningful decision-making profiles characterised by different combinations of cognitive styles and ethical prioritisation patterns: analytically oriented decision-makers prioritising health gains; intuitive, context-sensitive decision-makers balancing clinical and social criteria; heuristic-driven decision-makers relying on simpler or less differentiated heuristics. These findings demonstrate that, within this sample, healthcare prioritisation preferences are shaped by systematic variations in decision style rather than a single moral or rational framework. By linking behavioural heterogeneity with ethical decision-making, this study contributes to theoretical debates on healthcare rationing and demonstrates the value of clustering techniques for uncovering latent structures in complex decision data. The results provide insights relevant for the design of decision-support systems and rationing policies, which may be adapted to accommodate heterogeneous decision styles in comparable settings.

Keywords: healthcare resource allocation; decision-making styles; social psychology; health economics and management; prioritisation criteria; machine learning; clustering analysis

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1. Introduction

Scarcity of healthcare resources is a defining feature of all health systems, irrespective of their level of development or financing arrangements. Because demands for healthcare systematically exceed available resources, societies are inevitably confronted with difficult choices regarding who should receive treatment, when, and under what conditions. These choices raise fundamental questions of distributive justice and lie at the core of health economics and health policy analysis [1,2]. From a normative economic perspective, priority setting in healthcare has traditionally been analysed through competing principles of distributive justice. Utilitarian approaches emphasise the maximisation of total health gains, often operationalised through measures such as life-years gained or Quality-Adjusted Life Years (QALYs) [3,4]. Alternative perspectives stress equity considerations, including severity of illness, need, or concern for the worse-off, reflecting prioritising or egalitarian views [5]. In practice, healthcare decision-making rarely relies on a single principle, and real-world allocation often reflects implicit trade-offs between efficiency and equity [6,7].

While normative frameworks provide guidance on how healthcare resources ought to be allocated, there is growing recognition that actual decisions, whether made by policymakers, clinicians, or citizens, are also shaped by behavioural and psychological factors [8,9]. Insights from behavioural economics challenge the assumption of fully rational, consistent decision-makers, highlighting the roles of heuristics, emotions, and individual decision styles in complex, morally charged contexts [10,11]. In the context of health-related choices, empirical evidence suggests that individuals' preferences over distributive criteria may vary systematically with their cognitive and decision-making characteristics [12,13]. Furthermore, healthcare allocation decisions have been shown to be influenced by psychological and social factors, such as societal preferences for directing scarce resources towards children or younger people, stereotyping and social categorization [14,15].

Recent literature has increasingly explored public preferences for healthcare priority setting using hypothetical choice scenarios, asking respondents to choose between patients who differ in attributes such as expected health gains, age, severity of illness, or social roles [5,16,17]. While this literature provides important insights into societal values, most studies rely on aggregate analyses that implicitly assume homogeneity among respondents. Consequently, less attention has been paid to identifying latent profiles of decision-makers that combine cognitive styles and socio-demographic characteristics, and to examining how these profiles systematically influence allocation choices. Understanding this heterogeneity is particularly relevant for health policy for two major reasons. First, the acceptability and legitimacy of rationing decisions depend not only on their consistency with normative principles but also on their alignment with citizens' values and decision processes [18,19]. Second, although decision-making styles are widely regarded as a central component of effective decision processes, substantial evidence shows that individuals differ markedly in how they approach and resolve choices. Rather than relying on a single, stable style, most people display flexibility, adapting their decision strategies to the demands and stakes of a given situation [20]. This situational adjustment is particularly evident in health-related contexts, where perceived threat and potential consequences for survival tend to elicit more effortful and maximizing approaches [21]. Studying decision-making styles as a systematic source of heterogeneity, therefore, offers critical insights into why and how different individuals make divergent allocation decisions and helps inform policy designs that are both ethically defensible and responsive to heterogeneous decision processes in the population. Building on the theoretical and empirical considerations outlined above, this study aims to identify and characterise distinct individual profiles within the sample by integrating three complementary dimensions of information: socio-demographic attributes, decision-making styles, and preferences regarding healthcare rationing. By jointly analysing background characteristics, cognitive and behavioural tendencies, and normative preferences in resource allocation, the study seeks to uncover latent patterns that explain how individuals differ in ethically complex and scarcity-driven contexts. The resulting profiles offer a structured representation of decision-making heterogeneity observed in this sample, enabling a more nuanced understanding of how personal characteristics and moral intuitions interact in prioritisation scenarios. This interdisciplinary approach combines

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insights from health economics, social psychology, and data-driven computational methods to provide evidence that is informative for the design and potential social acceptability of rationing policies in similar contexts.

Recent advances in data science and machine learning offer powerful tools to address this limitation. Unsupervised learning techniques, such as clustering algorithms, enable the identification of latent groups within heterogeneous populations based on patterns in high-dimensional data, without imposing a priori assumptions about group membership [22,23]. In health research, clustering methods have increasingly been used to uncover meaningful profiles of patients or behaviours, supporting more nuanced and data-driven analyses of complex phenomena [24–30].

Against this background, survey data collected under hypothetical scenarios of healthcare resource scarcity were analysed using clustering techniques to identify distinct decision-maker profiles based on their decision styles and socio-demographic characteristics. These profiles were subsequently examined to explore whether they differ in their prioritisation choices under conditions of scarcity. By combining computational methods with economic and psychological theory, this study contributes to a deeper understanding of heterogeneity in healthcare prioritisation preferences and provides evidence relevant to the social acceptability and transparency of rationing decisions in health policy.

This study advances existing research by integrating cognitive decision-making styles with concrete ethical prioritisation patterns in healthcare rationing, an empirical connection that has not been systematically examined in prior work. While decision styles and allocation principles have each been extensively studied within their respective fields, they have rarely been analysed jointly within the same empirical framework. Importantly, the objective of this study is not to reproduce established psychological typologies, but to examine how cognitive styles interact with ethically salient trade-offs as observed in our sample under conditions of resource scarcity. By combining decision-style indicators with multidimensional prioritisation responses through data-driven clustering techniques, we identify latent decision-making configurations that emerge from the structure of allocation choices themselves. These profiles do not simply mirror predefined categories but reflect integrated cognitive–ethical patterns specific to the rationing scenarios studied. By linking behavioural heterogeneity to ethically relevant allocation preferences, the study advances understanding of how prioritisation judgments are formed and provides an interdisciplinary contribution spanning health economics, social psychology, and computational modelling.

2. Related Work

Recent advances in healthcare analytics have increasingly leveraged data-driven and computational methods to support decision-making under conditions of resource scarcity. Within this literature, unsupervised learning techniques, particularly clustering, have played a central role in extracting structure from complex, high-dimensional healthcare data and supporting decision-support systems in uncertain and constrained environments. Clustering methods have been widely applied across healthcare domains, including patient stratification, demand forecasting, logistics optimisation, and operational planning. A variety of algorithmic families have been explored, such as centroid-based, density-based, connectivity-based, and fuzzy clustering approaches, each addressing specific challenges related to scalability, non-linearity, and data incompleteness [31,32].

These techniques enable the identification of latent groups without imposing predefined labels, making them especially suitable for exploratory analysis in heterogeneous populations and complex decision contexts. In the context of healthcare resource allocation, clustering has been used to enhance efficiency and robustness under uncertainty.

For example, demand scenarios have been grouped using K-means clustering within two-stage stochastic programming models to reduce computational complexity and improve allocation performance under uncertain resource requirements [33].

Similarly, improved clustering algorithms have been applied to optimise blood donor management and distribution systems, supporting emergency response and resource coordination [34].

These studies demonstrate the value of clustering as a computational tool for managing uncertainty and supporting optimisation in resource-constrained healthcare settings. Beyond operational optimisation, clustering has also been employed as a profiling mechanism to characterise heterogeneous actors within healthcare systems. Prior research has used unsupervised learning to segment patients, clinicians, or organisational units based on behavioural, contextual, or performance-related variables, contributing to more adaptive and personalised decision-support frameworks [35,36].

Such profiling approaches support the design of systems that are responsive to heterogeneity rather than relying on average or representative decision-makers. Parallel developments in behavioural and cognitive research indicate that individuals exhibit systematic and relatively stable differences in how they process information and approach decisions under uncertainty. While decision-making styles have been extensively studied in psychology, their integration into computational clustering frameworks applied to healthcare rationing remains limited [27].

Existing computational studies tend to prioritise clinical, logistical, or operational variables, often abstracting from the cognitive and behavioural processes that shape human allocation decisions. This study addresses this gap by integrating decision-making styles and socio-demographic attributes into a clustering-based profiling framework applied to healthcare rationing scenarios. By combining behavioural data with unsupervised machine learning techniques, the proposed approach extends existing computational models of healthcare resource allocation beyond purely algorithmic or normative assumptions. It demonstrates how clustering can be used not only for optimisation or prediction, but also for uncovering latent behavioural profiles that inform the design of explainable, human-centred, and behaviourally aware decision-support systems under conditions of scarcity.

3. Proposed Method

The methodological framework of this study follows a structured, data-driven pipeline designed to ensure the robustness, transparency, and interpretability of the profiling analysis. The framework comprises successive stages, including data collection and variable description, data preprocessing, clustering-based profiling, and validation procedures. Each stage is described in detail in the following subsections. Figure 1 illustrates the complete workflow of the study, from data collection and preprocessing to feature extraction, clustering, and profile interpretation. Each step is numbered sequentially, highlighting the inputs, transformations, and outputs, providing a clear overview of the analytical process used to identify decision-making profiles under healthcare resource scarcity.

3.1. Data Collection and Variable Description

Data were collected between May and September 2025 through an online questionnaire administered to adult residents in Portugal. The survey was disseminated via social media platforms, and undergraduate students from a Portuguese university participated in the data collection as part of a course assignment helping distribute the questionnaire link. A total of 3084 valid responses were collected and included in the analysis. Participation in the study was voluntary and anonymous. All respondents were informed about the purpose of the study and provided informed consent prior to participation. No personally

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identifiable information was collected, and the study complied with applicable ethical standards for research involving human participants.

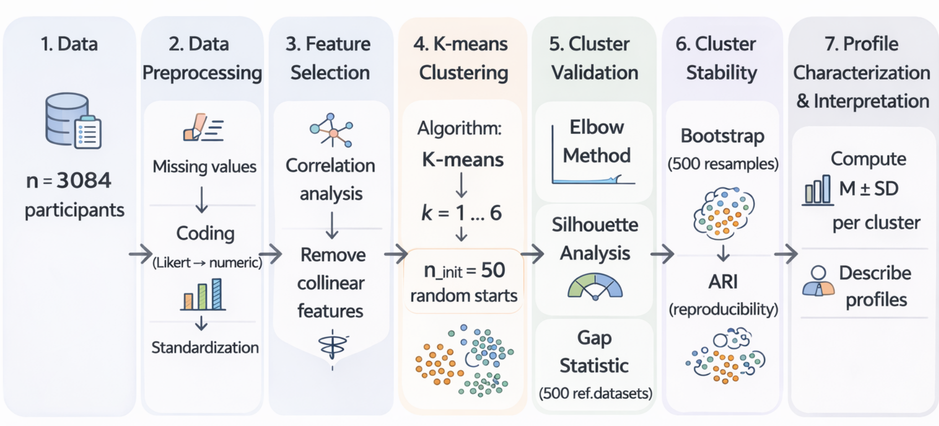

Figure 1. Analytical Pipeline Diagram.

The questionnaire consisted of three main sections. The first section collected socio-demographic information, including age, sex, marital status, educational attainment, employment status, and political orientation. These variables were later used to characterise respondents and to support the construction of decision-maker profiles. The second section measured respondents' decision-making styles using a reduced, adapted version of the General Decision-Making Style (GDMS) questionnaire, originally developed by Scott and Bruce (1995) [37]. Participants were presented with ten statements and asked to indicate their level of agreement on a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Two statements were used to assess each of the five decision-making styles: rational, intuitive, dependent, avoidant, and spontaneous.

The rational decision-making style reflects a systematic and analytical approach to choice, characterised by careful evaluation of information and consideration of multiple alternatives. This style was assessed through agreement with statements such as "*The decisions I make require careful thought*" and "*I consider several options when making a decision*". This style is closely aligned with normative models of decision-making that assume deliberation and consistency. In contrast, the intuitive decision-making style captures reliance on feelings, instincts, and experience-based judgments, particularly in complex or ambiguous situations. It was measured using statements including "*When making a decision, I tend to rely on my intuition*" and "*I base my decisions on my instincts*", in line with dual-process accounts of cognition [10]. The dependent decision-making style reflects a tendency to seek advice, reassurance, or support from others when facing important decisions, indicating a preference for shared responsibility under uncertainty or morally charged contexts. This style was measured through agreement with statements such as "*I rely on the advice of others when making important decisions*" and "*I usually need help from other people when making important decisions*". The avoidant decision-making style is characterised by reluctance to engage with decision-making tasks, often expressed as procrastination or postponement when confronted with difficult trade-offs. It was assessed using statements such as "*I usually procrastinate when I have to make an important decision*" and "*I delay making decisions whenever possible*". Finally, the spontaneous decision-making style reflects a preference for rapid and impulsive choices, prioritising speed over deliberation. This style was measured using statements such as "*I usually make decisions in the heat of the moment*" and "*I generally make decisions instantly*".

Internal consistency for each of the five decision-making styles was assessed using Cronbach's alpha. Despite the scale being a shortened/adapted version of Scott & Bruce

(1995) [37], the reliability indices indicate acceptable consistency: spontaneous ($\alpha = 0.688$), intuitive ($\alpha = 0.690$), dependent ($\alpha = 0.630$), avoidant ($\alpha = 0.620$), and rational ($\alpha = 0.672$). These results support the use of the scale to capture meaningful individual differences in decision-making styles in the context of healthcare rationing.

Consistent with the established literature, decision-making styles were conceptualised as relatively stable patterns in how individuals process information and approach choices under uncertainty [37]. Rather than focusing on decision outcomes, this framework emphasises the underlying cognitive and behavioural processes guiding choice. Incorporating decision-making styles into the analysis provides a behavioural foundation for subsequent clustering procedures and enables the identification of latent decision-maker profiles in ethically complex, scarcity-driven healthcare allocation contexts.

The third section elicited respondents' preferences regarding healthcare rationing criteria through a set of twenty hypothetical scarcity scenarios, following a structured design used elsewhere and conveniently described [38]. In each scenario, respondents were required to prioritise between two patients under conditions of constrained healthcare resources. The paired patients differed only with respect to a specific and controlled set of attributes, allowing the isolation of individual prioritisation criteria. These attributes comprised health-related characteristics, such as potential health gains measured in life-years or quality of life, and severity of health status assessed in terms of pain and risk of death, as well as personal and social characteristics, including age, parental status, risk-related behaviour, waiting time, and instrumental value to society.

To quantify support for each criterion, we derived criterion-level scores from the scenario choices: for each participant, the proportion of decisions consistent with each prioritisation criterion was calculated, producing a score representing relative endorsement of that criterion. These individual scores were subsequently averaged across participants within each cluster to obtain profile-level mean importance scores, which are used to characterise differences in prioritisation patterns across the decision-maker profiles identified through clustering. This procedure allows the integration of scenario-based behavioural data with cognitive and socio-demographic dimensions, forming the basis for the identification of latent decision-making profiles.

Based on the collected variables, the study applies clustering techniques to identify latent decision-maker profiles, integrating socio-demographic attributes and decision-style dimensions.

3.2. Data Pre-Processing

Prior to the analytical phase, several data pre-processing steps were applied to ensure data quality, consistency, and suitability for profiling and clustering analyses. These procedures were designed to harmonize heterogeneous data sources, reduce noise, and minimize potential biases introduced during data collection.

First, the dataset was inspected for missing, incomplete, or inconsistent responses. Records containing excessive missing values were excluded from the analysis, while isolated missing entries were handled using appropriate imputation strategies depending on the variable type. Categorical variables were completed using mode-based imputation, whereas numerical variables were imputed using median values to reduce sensitivity to outliers. Second, categorical variables, including socio-demographic attributes and decision-related preferences, were encoded into numerical representations suitable for statistical analysis. Ordinal variables were preserved according to their intrinsic ordering, while nominal variables were transformed using one-hot encoding where necessary. Special attention was given to decision criteria variables to ensure that higher values consistently reflected stronger agreement or higher prioritization. Third, numerical variables were standardized to ensure comparability across different measurement scales. Z-score normalization was applied to continuous variables related to decision-style dimensions, preventing attributes with larger numeric ranges from disproportionately influencing distance-based clustering algorithms.

Outlier detection was then performed using Interquartile Range (IQR) analysis. Extreme values were examined to distinguish between legitimate but rare responses and data entry errors. Only implausible observations were removed to preserve the natural variability of ethical and decision-making preferences. Finally, prior to clustering, multicollinearity among variables was assessed using correlation analysis. Highly correlated features were carefully reviewed to avoid redundancy and instability in the profiling process. Where necessary, correlated variables were retained only if they contributed distinct theoretical or interpretative value. The resulting pre-processed dataset provided a robust and coherent foundation for subsequent clustering and profile extraction.

3.3. Profiling

Profiling refers to the systematic identification of groups of individuals who share similar characteristics, behaviours, or decision-making patterns, allowing researchers to uncover latent structures within complex datasets. In the context of this study, decision-making profiling aims to capture heterogeneity in how individuals approach ethical and scarcity-driven choices. The methodology combines descriptive statistical analysis with unsupervised clustering techniques to identify homogeneous groups based on decision-style dimensions and socio-demographic attributes, and subsequently examines how these profiles relate to preferences for rationing criteria. By integrating behavioral tendencies with normative considerations, this approach provides a data-driven and conceptually grounded framework for understanding variation in decision-making under conditions of limited resources.

3.3.1. Descriptive Analysis of Decision-Style Characteristics

The first stage of the methodology involved a comprehensive descriptive statistical analysis of the socio-demographic variables and decision-style dimensions. This step aimed to explore the underlying structure of the data and identify salient patterns in decision-making behaviour prior to any model-driven grouping. Measures of central tendency, dispersion, and distribution shape were examined to assess the relative prominence of analytical, intuitive, and low-engagement tendencies across the sample. This descriptive analysis also supported the evaluation of decision-style constructs by verifying whether observed response patterns were consistent with theoretical expectations from the decision-making literature. Grounding the clustering process in empirically observed tendencies ensured that profile construction was informed by substantive behavioural characteristics, rather than being purely algorithmic.

3.3.2. Clustering-Based Profile Identification

Unsupervised clustering was selected as the principal method to identify latent decision-making profiles without imposing preconceived group boundaries.

K-Means clustering was selected due to its interpretability, scalability, and established use in behavioural profiling research. To determine the optimal number of clusters (k), the following complementary criteria were used: (i) the Elbow Method, evaluating the Within-Cluster Sum of Squares (WCSS) across increasing k values; (ii) Silhouette Analysis, assessing cluster cohesion and separation; and (iii) Gap Statistic, comparing observed clustering performance with a null reference distribution. Triangulating these metrics allowed for a robust selection of the final cluster solution, which balanced statistical coherence with practical interpretability.

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The goal of K-means clustering is to partition n participants into k clusters, $C_1, \ldots, C_k$, by minimizing the WCSS:

$$\text{WCSS} = \sum_{r=1}^{k} \sum_{x_i \in C_r} \|x_i - \mu_r\|^2$$

where

- C_r is the set of participants assigned to cluster r;
- $\mu_r = \frac{1}{|C_r|} \sum_{x_i \in C_r} x_i$ is the centroid of cluster r;
- x_i is the vector of criterion scores for participant i.

Cluster formation relied exclusively on standardized decision-style dimensions and socio-demographic attributes. Variables representing healthcare rationing preferences were not included in the clustering procedure. This ensures that the identification of latent profiles is independent of the criterion-level scores and avoids circularity in subsequent interpretation. Once clusters were determined, profiles were characterized using centroid analysis, featuring inspection of standardized scores at cluster centroids to determine dominant decision-style tendencies; demographic profiling, involving calculation of cluster-specific demographic distributions (e.g., gender, age group, professional experience); and statistical summaries, i.e., a comparison of means and variances of key variables across clusters to identify distinguishing traits.

Profiles were given interpretive labels reflecting their dominant decision-style dimensions (e.g., rational–analytical, intuitive–context-sensitive, and heuristic-driven), facilitating a structured understanding of how cognitive styles manifest in heterogeneous approaches to decision-making under scarcity.

K-means was selected for three primary reasons:

1. Suitability to the Data Structure: The variables used for clustering consist of continuous Likert-scale measurements treated as approximately interval-level variables, a common and accepted practice in behavioural and decision-science research. K-means is well-suited for partitioning continuous multivariate data into compact, spherical clusters by minimizing WCSS. Because our objective was to identify internally cohesive and externally distinct decision-making profiles, variance minimization was theoretically aligned with the research aim.
2. Interpretability and Theoretical Alignment: Our study aims to derive interpretable behavioural profiles. K-means produces centroid-based clusters, which allow straightforward interpretation in terms of mean score patterns across decision criteria. This centroid representation facilitates theoretical mapping between statistical clusters and substantive decision-making styles. More complex model-based approaches (e.g., Gaussian Mixture Models) would introduce additional distributional assumptions without substantially improving interpretability in this context.
3. Empirical Robustness Checks: To ensure that the choice of K-means did not bias results, we evaluated cluster validity using a triangulated approach (Elbow, Silhouette, and Gap Statistic). All criteria converged on a three-cluster solution, suggesting structural stability independent of any single diagnostic metric.

To ensure the robustness of the identified K-means solution, we implemented two complementary stability checks: (i) Multiple Random Initializations and (ii) Bootstrap-Based Reproducibility.

K-means clustering is sensitive to the choice of initial centroids. For each tested value of k, the algorithm was executed with n_init = 50 random starts. The solution with the lowest total WCSS was retained. Across repeated runs, the three-cluster configuration consistently converged to the same partition, demonstrating stability with respect to initialization.

To evaluate the sensitivity of cluster assignments to sampling variability, we generated 500 bootstrap resamples of the dataset (n = 3084, sampling with replacement) and applied K-means clustering with k = 3 to each resample. Agreement between the original solution and each bootstrap replication was quantified using the Adjusted Rand Index (ARI), which corrects for chance similarity. This procedure ensures that the clustering solution is reproducible under minor perturbations of the data.

Internal validation metrics (Elbow, Silhouette, Gap Statistic) assess cohesion and separation but do not evaluate reproducibility. By combining multiple random initializations and bootstrap resampling, we ensure that the identified profiles reflect genuine structure in the data rather than artefacts of the algorithm or sample idiosyncrasies.

3.3.3. Association Between Profiles and Rationing Criteria

After clusters were established, the analysis examined how profiles relate to preferences for different healthcare rationing criteria. For this purpose, mean importance scores were computed for each criterion within each profile. These scores were derived from respondents' choices in the twenty hypothetical scarcity scenarios: for each participant, the proportion of decisions consistent with a given criterion was calculated, producing a criterion-level score representing relative support. Aggregating these scores across respondents in each cluster yielded profile-level mean importance scores, which summarise the central tendency of ethical prioritisation among individuals with similar decision-making styles.

Let $X \in \mathbb{R}^{n \times p}$ denote the data matrix, where n is the number of participants ($n = 3084$) and p is the number of decision criteria. Each row $x_i \in \mathbb{R}^p$ represents the scores of participant i across all criteria. For each criterion $j \in \{1, \ldots, p\}$, the weighted mean of scores is defined as

$$\bar{X}_j = \frac{\sum_{i=1}^{n} w_i x_{ij}}{\sum_{i=1}^{n} w_i}$$

where

- x_{ij} is the score of participant i on criterion j;
- w_i is the weight assigned to participant i (for unweighted mean, $w_i = 1$);
- $\bar{X}_j$ is the weighted mean of criterion j.

The corresponding weighted standard deviation is

$$SD_j = \sqrt{\frac{\sum_{i=1}^{n} w_i (x_{ij} - \bar{X}_j)^2}{\sum_{i=1}^{n} w_i}}$$

By separating the clustering input variables from the post hoc use of prioritisation data, the methodology maintains conceptual and statistical independence between profile construction and ethical preference description. This ensures that the profiles represent emergent patterns in decision styles and socio-demographic characteristics, while the subsequent characterisation in terms of healthcare prioritisation provides an interpretable, descriptive account of ethical preferences across profiles.

4. Results

This section presents the empirical results of the study, structured in accordance with the analytical steps defined in the methodology. First, an exploratory data analysis is used to characterize the distribution of decision-making styles across sociodemographic and contextual variables. Subsequently, a clustering approach is applied to identify latent decision-making profiles based on these dimensions. Finally, the identified profiles are examined in relation to rationing criteria, allowing for a systematic assessment of how

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different decision-making styles and socio-economic characteristics are associated with distinct ethical prioritization patterns under conditions of resource scarcity.

4.1. Descriptive Analysis of Decision-Style Characteristics

Table 1 presents the descriptive distribution of decision-making styles across key sociodemographic and contextual variables.

Gender differences indicate that male respondents exhibit a higher relative prevalence of intuitive and spontaneous decision-making styles, whereas female respondents show a stronger inclination toward rational decision-making. Dependent and avoidant tendencies are more pronounced among female participants, suggesting a greater reliance on structured guidance and risk-averse strategies.

With respect to marital status, married respondents present the highest proportion of intuitive decision-making, combined with relatively low avoidant tendencies, indicating confidence in situational judgment. In contrast, widowed participants show increased dependent and spontaneous scores and the lowest rational orientation, which may reflect heightened uncertainty or vulnerability in decision contexts. Divorced or separated respondents demonstrate the strongest rational orientation, paired with low dependent and avoidant tendencies, suggesting a preference for autonomous and deliberative decision-making.

Clear gradients emerge across levels of education. Lower educational attainment is associated with higher spontaneous and avoidant tendencies, whereas higher education levels, particularly master's and doctoral degrees, are strongly associated with rational decision-making. Notably, respondents with postgraduate education exhibit the lowest dependent and avoidant scores, indicating greater confidence in independent ethical reasoning. These findings support the role of formal education in shaping structured and analytical decision-making processes within the sample of Portuguese respondents.

Regarding professional situation, employed respondents show the highest rational orientation and the lowest avoidant scores, consistent with regular exposure to structured decision environments. Retired and unemployed respondents display higher spontaneous and dependent tendencies and markedly lower rational scores, potentially reflecting reduced engagement with formal decision-making frameworks. Students and working students occupy an intermediate position, combining moderate rationality with elevated spontaneous and avoidant traits.

Age-related patterns further reinforce these trends. Generation X respondents demonstrate the strongest rational orientation and the lowest spontaneous and avoidant tendencies, suggesting mature and experience-based decision-making styles. In contrast, Baby Boomers and Generation Z exhibit higher dependent and spontaneous scores, pointing to either reliance on established norms (older cohorts) or situational reactivity (younger cohorts). Generation Y shows a balanced profile, with relatively high rational and intuitive orientations.

Finally, political orientation reveals more nuanced differences. Respondents identifying with the political center or right display stronger rational decision-making tendencies, whereas those on the left show elevated avoidant scores. Individuals without a declared political orientation exhibit the highest intuitive and dependent tendencies and the lowest rational scores, indicating less structured ethical positioning in decision-making contexts.

Taken together, these descriptive results provide robust empirical evidence that decision-making styles seem to be associated with sociodemographic, educational, and contextual factors. Importantly, these patterns substantiate the relevance of the clustering results presented in the subsequent sections, offering a strong descriptive foundation for the identification of latent decision-making profiles.

Table 1. Descriptive statistics concerning decision-making styles.

	Dependent	Spontaneous	Avoidant	Intuitive	Rational
Gender					
M	6.56	17.12	4.17	29.98	42.16
F	7.32	10.60	6.26	28.42	47.40
Marital Status					
Married/Common-law marriage	6.48	10.18	4.16	30.8	48.38
Divorced/Separated	4.95	16.83	3.96	24.75	49.5
Single	7.3	14.26	7.13	26.85	44.46
Widowed	12.24	19.39	7.14	24.49	36.73
Other	7.63	14.48	4.31	32.88	40.7
Level of Education					
1st Cycle (4th grade)	7.75	21.71	8.53	37.98	24.03
2nd Cycle (6th grade)	7.46	32.84	4.48	32.84	22.39
3rd Cycle (9th grade)	4.55	21.59	8.52	29.55	35.80
Bachelor's Degree	6.45	6.45	8.06	35.48	43.55
Doctorate	2.27	15.91	2.27	29.55	50.00
Secondary Education	6.88	13.77	5.14	31. 67	42.54
Licentiate Degree	8.16	9.83	5.25	24.25	52.51
Master's Degree	6.98	6.59	4.26	22.87	59.3
Other	5.48	17.81	4.11	32.88	39.73
Professional Situation					
Employed	6.1	10.77	3.73	29.61	49.8
Student	7.95	13.28	6.84	27.87	44.06
Retired	8.37	20.92	7.11	30.54	33.05
Working Student	7.48	18.37	9.52	23.81	40.82
Unemployed	7.79	17.53	5.84	32.47	36.36
Other	8.11	16.22	5.41	31.08	39.19
Age					
Generation BB	7.8	16.59	6.59	28.78	40
Generation X	6.67	6.68	3.11	30.43	53.11
Generation Y	4.93	14.04	3.98	31.31	45.73
Generation Z	7.78	14.7	6.59	27.68	43.25
Political Orientation					
Center	7.83	12.54	4.8	27.85	46.98
Right	6.02	15.32	4.65	28.18	45.83
Left	6.24	10.88	8.16	28.64	46.08
No Political Option	7.78	14.24	4.64	32.62	40.73

4.2. Determination of the Optimal Number of Clusters

To ensure a robust and transparent selection of the optimal number of clusters, we employed a triangulated validation strategy combining the Elbow Method, Silhouette Analysis, and the Gap Statistic. This multi-criteria approach reduces reliance on any single heuristic and enhances methodological rigour.

Elbow Method: We computed the WCSS for k values ranging from 1 to 6. As shown in Figure 2, the WCSS curve exhibits a pronounced inflection at $k = 3$. Beyond this point, the marginal reduction in WCSS diminishes substantially, indicating decreasing returns in explanatory power with increasing model complexity. This pattern is consistent with the classical interpretation of the Elbow heuristic, where the optimal k corresponds to the point at which additional clusters fail to meaningfully improve intra-cluster compactness.

Silhouette Analysis: To further assess cluster cohesion and separation, we calculated the average silhouette coefficient for each k ($k \geq 2$). The silhouette metric evaluates how well each observation fits within its assigned cluster relative to neighbouring clusters, with values approaching 1 indicating strong separation. As reported in Figure 3, the highest average silhouette score was observed at $k = 3$, suggesting that this configuration achieves the best balance between internal cohesion and external separation among the tested solutions.

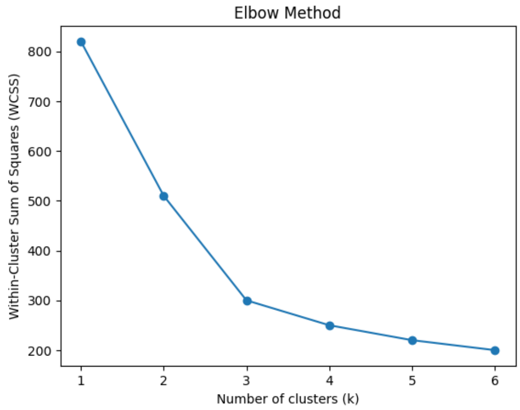

Figure 2. Elbow Method for determining the optimal number of clusters.

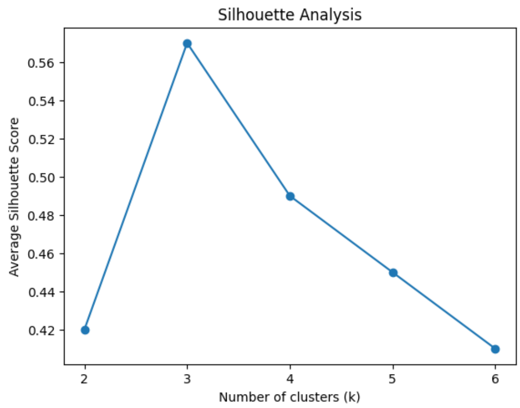

Figure 3. Silhouette analysis for cluster validation.

Gap Statistic: We also computed the Gap Statistic using 500 Monte Carlo reference datasets to compare clustering performance against a null distribution. The Gap Statistic measures the deviation between observed clustering structure and that expected under randomness. The largest Gap value was obtained at $k = 3$, indicating that the three-cluster solution provides the strongest evidence of non-random structure within the data. Table 2 summarises the results of the determination of the optimal number of clusters.

Table 2. Summary of clustering validation metrics across tested values of k. The best results are highlighted in bold.

k	WCSS	Average Silhouette	Gap Statistic
1	820	–	0.12
2	510	0.42	0.31
3	300	**0.57**	**0.48**
4	250	0.49	0.44
5	220	0.45	0.39
6	200	0.41	0.35

Triangulated Decision: Across all three validation criteria, k = 3 consistently emerged as the optimal solution. The convergence of the Elbow heuristic (structural inflection), the Silhouette coefficient (maximum cohesion–separation balance), and the Gap Statistic (largest deviation from null expectation) provides convergent validity for the three-profile configuration. This triangulated approach aligns with best practices in unsupervised learning, where reliance on multiple complementary diagnostics mitigates subjectivity inherent in any single metric. The combined evidence supports the retention of three distinct decision-making profiles for subsequent analysis.

The robustness of the three-cluster solution was confirmed through multiple approaches. First, K-means clustering with 50 random initializations consistently converged to the same partition, indicating minimal sensitivity to centroid initialization. Second, a bootstrap analysis with 500 resamples of the dataset (n = 3084) was performed, and cluster agreement with the original solution was quantified using the ARI. The average ARI across all bootstrap replications was 0.91 (SD = 0.03), indicating high reproducibility of cluster assignments under sampling variability. These results demonstrate that the identified decision-making profiles are stable, robust, and not artefacts of random initialization or sample perturbations.

4.3. Clustering Analysis of Decision Styles and Healthcare Prioritisation Criteria

Following the descriptive characterisation of decision-style dimensions, an unsupervised clustering analysis was conducted to identify latent decision-making profiles within the sample. The clustering was applied to standardised decision-style dimensions and socio-demographic attributes, allowing profiles to emerge naturally from observed patterns without imposing predefined assumptions regarding their number or composition. The resulting solution revealed three distinct and internally consistent profiles, each exhibiting a coherent configuration across cognitive, behavioural, and normative dimensions. The clusters demonstrated clear separation between profiles and sufficient within-cluster homogeneity, supporting their robustness and interpretability.

Figure 4 presents a radar chart of the three profiles, illustrating their multidimensional decision-making patterns across the five decision-style dimensions (rational, intuitive, dependent, spontaneous, and avoidant). The figure shows that decision-making in healthcare resource allocation cannot be adequately captured by a single dominant dimension; rather, it emerges from specific combinations of decision-style characteristics.

Figure 5 presents the same profiles in terms of post hoc mean importance scores for healthcare prioritisation criteria, providing an interpretive view of how each profile values different clinical, social, and moral considerations.

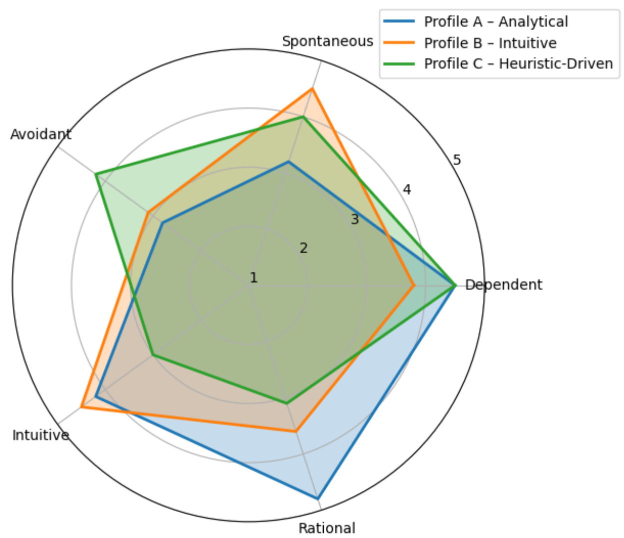

Figure 4. Radar chart of decision-style dimensions across the three profiles. High scores in rational and intuitive dimensions characterize Profile A (analytical), high intuitive and spontaneous scores characterize Profile B (intuitive), and elevated dependent and avoidant scores characterize Profile C (heuristic-driven). The decision style dimensions use a scale between 1 and 5.

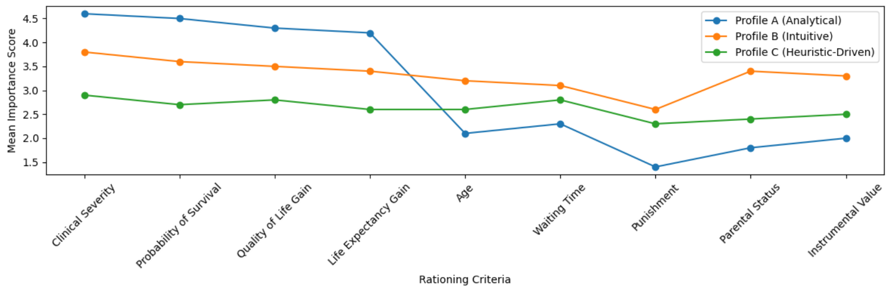

Figure 5. Mean importance scores of rationing criteria across decision-making profiles. The figure illustrates systematic differences in the prioritization of clinical, social, and moral criteria among analytically oriented, intuitively oriented, and heuristic-driven decision-making profiles.

It is important to note that comparisons of healthcare prioritisation preferences across profiles are descriptive and post hoc. No inferential statistical tests (e.g., *t*-tests, ANOVA) were conducted to compare mean importance scores between clusters. The reported means and standard deviations illustrate observed patterns within this sample and are intended to provide interpretive insights into how decision styles relate to prioritisation preferences, without implying population-level statistical inference. The reported means and standard deviations illustrate observed patterns within this sample and are intended to provide interpretive insights into how decision styles relate to prioritisation preferences, without implying population-level statistical inference. The profiles are described as follows:

Profile A—Analytical Decision-Makers: High scores in rational and intuitive dimensions, low in dependent, spontaneous, and avoidant dimensions. Typically older, highly educated, and employed. Post hoc examination of prioritisation preferences shows strong emphasis on clinical criteria: clinical severity (M = 4.6, SD = 0.42), probability of survival (M = 4.5, SD = 0.47), quality-of-life gains (M = 4.3, SD = 0.50), life-expectancy gains (M = 4.2, SD = 0.53), and low weighting of social/moral criteria: parental status (M = 1.8, SD = 0.61), instrumental value (M = 2.0, SD = 0.58), punishment (M = 1.4, SD = 0.49). This steep prioritisation gradient reflects a predominantly utilitarian, evidence-based decision-making logic, where efficiency and expected health outcomes dominate ethical reasoning.

Profile B—Intuitive and Context-Sensitive Decision-Makers: Elevated intuitive and spontaneous scores, moderate rational tendencies. Generally younger, often with family responsibilities. Post hoc prioritisation patterns show balanced weighting: clinical criteria remain important (clinical severity (M = 3.8, SD = 0.72), probability of survival (M = 3.6, SD = 0.75)), but social/contextual criteria carry comparatively higher weight: age (M = 3.2, SD = 0.81), parental status (M = 3.4, SD = 0.77), instrumental value (M = 3.3, SD = 0.79). The flatter prioritisation curve suggests an ethical orientation that integrates clinical effectiveness with moral intuitions about social roles, vulnerability, and perceived societal contribution, consistent with a context-sensitive, intuitive decision-making style.

Profile C—Heuristic-Driven Decision-Makers: Lower rational and intuitive scores, higher dependent and avoidant tendencies. Often retired, unemployed, or with lower educational attainment. Post hoc prioritisation analysis shows minimal differentiation across criteria, with compressed mean scores: clinical severity (M = 2.9, SD = 0.83), punishment (M = 2.3, SD = 0.88), waiting time (M = 2.8, SD = 0.86), age (M = 2.6, SD = 0.84). This pattern reflects reliance on simple heuristics or low engagement with ethical trade-offs.

Interpretations regarding ethical orientation or engagement are inferential, based on observed prioritisation patterns rather than direct measures of motivation or moral reasoning.

5. Discussion

5.1. Interpretation of Findings

This study set out to explore heterogeneity in decision-making styles and support for prioritisation criteria in healthcare rationing contexts by adopting a profiling approach that integrates socio-demographic attributes and cognitive tendencies. Within this sample of Portuguese adults, the clustering analysis revealed three substantively meaningful decision-making profiles, each reflecting a coherent configuration of decision styles and associated ethical priorities. On the one hand, we identified a group of respondents, designated as analytical decision-makers (Profile A), who appear to be older, highly educated, and professionally active within this sample. Members of this profile tended to approach healthcare prioritisation in a structured and deliberative manner, with observed patterns suggesting a greater emphasis on clinical outcomes and overall health gains, consistent with a utilitarian ethical orientation. Social and contextual criteria appeared to play a relatively minor role in their decision-making. By contrast, intuitive and context-sensitive decision-makers (Profile B) were generally younger and often had family responsibilities in this sample. Their observed decision-making style was more flexible, integrating clinical effectiveness with social and contextual factors, such as age, parental status, and societal contributions. This profile showed a pluralistic ethical orientation, balancing efficiency with fairness and social sensitivity. Finally, a third profile, heuristic-driven decision-makers (Profile C), was characterised by lower engagement with complex decisions and often comprised retired, unemployed, or less educated participants. Their prioritisation patterns appeared less differentiated, reflecting reliance on simple heuristics or ambivalence when facing complex ethical trade-offs. Across this profile, both clinical and social criteria were considered, but no single principle clearly dominated.

These profiles are consistent with empirical evidence from psychological research on decision-making. The five dimensions of the GDMS inventory—rational, intuitive, dependent, avoidant, and spontaneous—have been validated across diverse populations and contexts, showing that individuals rarely rely on a single style, but rather manifest combinations of styles that form distinct behavioural patterns [37]. In health-related decision-making, these styles have been linked to real-world choices: for example, spontaneous or dependent tendencies increase participation in preventive interventions, whereas avoidant tendencies are associated with indecision or non-participation in provider choice [39,40]. Our findings suggest that combinations of decision styles are associated with differential weighting of patients' rationing criteria in this sample, highlighting systematic behavioural heterogeneity in ethically complex allocation tasks.

Comparisons with prior research on healthcare prioritisation further contextualise these findings. Systematic reviews indicate that public preferences generally integrate clinical outcomes with social and contextual considerations, though the relative importance varies by setting and elicitation method [41]. Within this Portuguese sample it seems that while efficiency and health gains are highly valued, there is also recognition of social roles and equity considerations [42]. Profile A mirrors the analytically oriented segment, prioritising utilitarian outcomes; Profile B reflects a context-sensitive group integrating social dimensions; and Profile C captures individuals with weaker engagement or heuristic-driven prioritisation, supporting the notion of heterogeneous ethical logics in public decision-making.

The findings of the present study also complement previous evidence [43], which highlighted that individuals' preferences for healthcare prioritisation are strongly shaped by their underlying human values. In that study, utilitarian and equity-based principles were more strongly endorsed by participants with a social and personal value orientation, demonstrating how cognitive, affective, and moral dimensions jointly influence prioritisation choices. The present analysis extends those findings by applying machine-learning clustering methods and incorporating socio-demographic factors, thereby providing additional evidence of robust latent profiles across samples and methodological approaches. Together, the two studies underscore the importance of considering psychological and socio-demographic characteristics when designing ethically robust and socially acceptable healthcare allocation frameworks.

5.2. Theoretical and Methodological Contributions

This study makes three main scientific contributions to the literature on healthcare prioritisation, behavioural decision-making, and computational modelling under resource scarcity. First, it establishes a novel empirical link between cognitive decision-making styles and ethical prioritisation criteria in healthcare rationing. While analytic–intuitive distinctions are well established in cognitive psychology and allocation principles such as equity or health maximisation are widely studied in health economics, these studies have rarely been integrated within a unified empirical framework. Our findings seem to indicate that ethical preferences in rationing scenarios systematically co-vary with dominant cognitive styles, revealing coherent decision profiles that combine processing modes with normative orientations. This challenges assumptions of homogeneous rationality in allocation models and provides evidence that multiple ethical logics coexist in structured and identifiable ways. Second, the study advances methodological innovation by applying unsupervised machine learning techniques to identify latent decision-making profiles grounded in multidimensional behavioural and socio-demographic data. Rather than relying on predefined typologies or normative classifications, the clustering framework uncovers emergent structures directly from observed prioritisation responses and decision-style indicators. This data-driven approach allows the detection of meaningful behavioural configurations, including profiles that do not align with classical analytic–intuitive continua but instead reflect context-specific heuristics shaped by scarcity environments. In doing so, the study demonstrates the analytical value of integrating psychological variables into computational profiling pipelines. Third, the study contributes to the computational modelling of ethical allocation decisions by reframing preference heterogeneity as a structured and modellable phenomenon. Instead of treating variation in prioritisation as statistical noise around a representative agent, the clustering results reveal distinct behavioural regimes within the decision population. This perspective advances the integration of behavioural theory into data-driven allocation modelling and provides a replicable methodological template for analysing heterogeneity in other complex and ethically sensitive decision domains.

5.3. Practical and Policy Implications

The findings also carry important practical implications for healthcare governance and decision-support design under conditions of scarcity. Recognition of distinct decision-making profiles can inform the development of multi-criteria prioritisation frameworks and digital decision-support systems that explicitly account for behavioural and moral diversity among stakeholders. Allocation tools that integrate clinical effectiveness with social and contextual criteria, while accommodating differences in cognitive processing, are more likely to enhance perceived fairness, transparency, and legitimacy. Moreover, the identification of low-engagement or heuristic-driven profiles highlights the need for simplified, guided, or structured deliberation mechanisms in high-stakes allocation environments. Rather than assuming uniform deliberative capacity, policymakers and institutional leaders can design communication strategies, training programmes, and escalation protocols that are responsive to heterogeneous decision logics. By embedding behavioural heterogeneity into allocation design, healthcare systems can move beyond purely normative or technocratic models toward more human-centred and behaviourally informed governance frameworks, ultimately strengthening trust and resilience in scarcity situations.

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged. First, the use of hypothetical scenarios and self-reported preferences may not fully capture real-world decision-making under healthcare scarcity, potentially limiting ecological validity. Second, the sample, while substantial, was recruited primarily through social networks and university channels, which may introduce selection bias and limit generalisability to the broader Portuguese population.

Certain groups, particularly individuals with limited digital access or weaker ties to academic environments, are likely underrepresented, which should be considered when interpreting the identified decision-making profiles. Third, the clustering analysis, although robust, relies on the selected decision-style dimensions and socio-demographic variables; inclusion of additional cognitive, affective, or contextual factors could reveal further heterogeneity. Moreover, the study reports descriptive patterns of decision-making profiles and their associated prioritisation preferences, without performing inferential statistical tests to formally compare profiles. Consequently, the reported contrasts should be interpreted as observed trends within this sample rather than statistically confirmed differences. Finally, although the decision-making styles were assessed using a reduced 10-item version of the GDMS (two items per style), which may not capture the full breadth of the original scale, internal consistency analyses indicate acceptable reliability for these brief indicators. Future research could address these limitations by employing larger and more diverse samples, exploring actual clinical or policy decision contexts, and integrating longitudinal or experimental designs to assess the stability of decision-making profiles over time and across scenarios. Such studies would deepen understanding of how psychological and value-based factors shape healthcare prioritisation and inform the design of ethically robust and socially acceptable allocation policies.

At last, future research could extend the present profiling approach by embedding the identified decision-making profiles into simulation-based or prescriptive allocation models, allowing the assessment of how profile-informed decisions influence the distribution of scarce healthcare resources.

6. Conclusions

This study highlights the heterogeneity of decision-making styles and ethical prioritisation in healthcare rationing, identifying three distinct profiles using unsupervised clustering techniques on decision-style and socio-demographic data within this sample of Portuguese adults. The findings demonstrate that individuals approach scarce resource allocation in diverse ways, underscoring the importance of considering psychological and value-based factors. Integrating machine learning methods with health economics and behavioural theory provides a powerful approach to uncover latent patterns and informs the design of decision-support tools and rationing policies that are fairer, more transparent, and sensitive to heterogeneous decision styles in comparable settings.

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Informed Consent Statement: Written informed consent was obtained from all participants before being included in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

QALYs	Quality-adjusted Life Years
GDMS	General Decision-Making Style
IQR	Interquartile Range
WCSS	Within-Cluster Sum of Squares
ARI	Adjusted Rand Index

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