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Multidimensional Profiling of Household Sustainable Consumption Scores

Abstract. *This paper presents a novel methodology for profiling household sustainable consumption scores using a survey of 2,117 households from Varna, Sofia, and Svishtov conducted in 2021–2022. Sustainable consumption is measured across five dimensions: a total score, housing, food, mobility, and product disposal. Traditional multiple regression cannot be applied due to multicollinearity and functional dependencies among these dimensions. To overcome this limitation, the study introduces a sub-segmentation approach closely related to clustering. Households are initially categorised into three clusters (high, middle, and low) based on their total score. This three-tier categorisation is then applied to each of the four specific consumption dimensions. By evaluating dimensions individually rather than relying solely on aggregate data or standard k-means clustering, this methodology successfully captures critical nuances—such as households with high total scores that still exhibit low sustainability in specific sub-dimensions. The result is a more granular and accurate framework for profiling sustainable consumer behaviour.*

Keywords: *sustainable consumption, household profiling, Bulgaria, sub-segmentation, cluster analysis, household behaviour.*

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1. Introduction

One of the defining characteristics of the marketing model for market development is its emphasis on customer orientation. Beneath this commonly cited principle lie a series of strategic actions, including the identification of relevant markets, the establishment of segmentation approaches and criteria, the delineation of market segments, and the subsequent analysis and evaluation of these segments. These steps culminate in the selection of target segments and the formulation of

positioning strategies. In highly competitive environments, such actions are indispensable for the development of effective marketing strategies.

From this perspective, market segmentation emerges as one of the most fundamental and frequently employed practices in marketing. As part of the process of identifying and analysing market segments, consumer profiling is often undertaken to gain deeper insights into customer behaviour. These profiles encompass a wide range of characteristics and serve as a valuable tool for refining market management strategies by enabling the application of more precise and targeted instruments. (Ntawanga et al., n.d.).

The authors of the present article have been engaged for many years in research on issues related to sustainable consumption. Across numerous publications, they have presented findings from a wide range of studies addressing various dimensions of sustainable consumption, including: the conceptualization and measurement of sustainable consumption (Kehayova-Stoycheva et al., 2023; Kehayova-Stoycheva et al., 2023); the examination of household knowledge regarding sustainable consumption (Kehayova-Stoycheva and Ivanov, 2022); the development of tools to address challenges in measuring sustainable consumption (Kehayova-Stoycheva and Vasilev, 2024); (Vasilev et al., 2022); the creation of a calculator for assessing sustainable consumption (Kehayova-Stoycheva and Vasilev, 2023); and the measurement of consumer responses to content related to sustainable consumption (Kehayova-Stoycheva and Nedev, 2024). Through these contributions, the authors have repeatedly demonstrated the contemporary relevance and importance of managing sustainable consumption.

The focus of the present article is the application of an alternative approach to profiling households based on their sustainable consumption outcomes. This focus is driven by the authors' curiosity to explore additional distinctions within established segments, particularly in cases where a conventional methodological framework proves inadequate.

Sustainable consumer behaviour is inherently non-uniform; individuals rarely exhibit identical levels of commitment across all consumption domains. While aggregate metrics reduce this real-world complexity to a single average, a multidimensional profiling approach preserves the behavioural heterogeneity ('the colourful spectrum of human choices') where high commitment in one domain coexists with lower engagement in another.

2. Literature Review

As previously noted, segmentation and the development of consumer profiles are long-established practices within the field of marketing. A wide array of segmentation criteria exists, varying according to numerous factors such as market type, timing of consumption, product usage contexts, consumer characteristics, and the nature of the data employed (Matta & Stalidis, 2024). Broadly speaking, consumer profiles can be classified into two principal categories: (1) static, also referred to as factual profiles, and (2) dynamic, also known as behavioural profiles

(Ntawanga et al., n.d.). Static (factual) profiles are based on specific consumer attributes—demographic, psychographic, socio-cultural, and behavioural—and are widely utilized in marketing practice. In contrast, dynamic (behavioural) profiling focuses on identifying associative patterns among diverse facts or circumstances. Within the study of sustainable consumer behaviour, static segmentation and profiling are more commonly applied.

The most frequently employed methods for delineating market segments in the specialized literature include factor analysis, cluster analysis, discriminant analysis, latent class analysis, and multiple regression-based models (Finisterra Do Paço et al., 2009; Verhoef & van Doorn, 2016; Sarti et al., 2018). In the present study, the profiles are static, derived from individual scores on sustainable consumption indices.

Measuring sustainable consumption is connected to leadership (Nacheva, 2026). Computer science helps in finding methods, but their application have to be analysed through the prism of marketing. Reliable data should be used for making further calculations (Azeroual et. al., 2026). Using machine learning techniques (Sulova et al., 2026) complex calculations may be made but real algorithms are needed (Stoyanova, M., 2020).

3. Methods (Model Specification)

3.1 Overview and Dataset Context

The dataset analysed in this study comprises $N = 2,117$ households surveyed across three Bulgarian cities (Varna, Sofia, and Svishtov) during 2021-2022. For each household $i \in \{1, \dots, N\}$, sustainable consumption is quantified across five continuous indices bounded on the interval $[0, 1]$:

- S_i^{Total} : Total Sustainability Index
- $X_{i,1}$: Housing Sustainability Index (H)
- $X_{i,2}$: Food Sustainability Index (F)
- $X_{i,3}$: Mobility Sustainability Index (M)
- $X_{i,4}$: Product Disposal Sustainability Index (P)

The detailed itemisation, survey design, and mathematical aggregation procedures used to calculate these indices are documented in Vasilev et al. (2023a), while the calculator execution and localized baseline assessments are published in Vasilev et al. (2023b) and Vasilev et al. (2023c), respectively.

3.2 Methodological Motivation: Limitations of Standard Modelling

A common analytical choice for examining multidimensional survey data is parametric regression. However, regressing the Total Sustainable Consumption Index (S^{Total}) onto its underlying dimensions—Housing (H), Food (F), Mobility (M), and Product Disposal (P)—is methodologically unsound. Because S^{Total} is calculated as a direct composite function of these four sub-dimensions, any regression model

predicting S^{Total} from H, F, M, and P would be tautological—merely attempting to statistically re-estimate the exact mathematical formula used to define the dependent variable in the first place. Consequently, such a regression provides no meaningful explanatory or predictive insight into household behaviour. Furthermore, standard aggregate regression models estimate population-average marginal effects, effectively smoothing out critical intra-household behavioural trade-offs. A single aggregate score can mask contrasting underlying habits—for instance, a household exhibiting highly sustainable housing practices paired with unsustainable mobility patterns. To overcome these structural limitations, our profiling framework bypasses direct regression modelling in favour of a multidimensional cross-classification approach. This preserves the granular, non-linear combinations across all four behavioural domains without forcing an artificial regression fit onto a mathematically constructed total index.

Direct parametric modelling (e.g., standard multiple linear regression or multivariate regression) of S_i^{Total} on the vector of component indices $\mathbf{X}_i = (\mathbf{X}_{i,1}, \mathbf{X}_{i,2}, \mathbf{X}_{i,3}, \mathbf{X}_{i,4})^T$ is unviable for two structural reasons:

- a) Functional Dependency: S_i^{Total} is mathematically synthesised directly as a weighted sum/composite of $\mathbf{X}_i$. Attempting regression analysis introduces deterministic functional dependencies.
- b) Multicollinearity: Strong inter-dimensional correlations violate independence assumptions, inflating standard errors and confounding coefficient interpretation.

While standard data-driven clustering techniques—such as single-tier k -means—can group households according to overall score proximity, they inherently smooth out intra-household trade-offs across dimensions. A household with a moderate aggregate score ($S_i^{\text{Total}} \approx 0.50$) may achieve it through uniform moderate behavior **(0.50, 0.50, 0.50, 0.50)** or through extreme compensation—such as high mobility sustainability paired with very low food sustainability **(0.90, 0.10, 0.80, 0.20)**. Aggregate metrics and single-level clustering mask these critical compensatory mechanics.

To prevent mathematical double-counting during cluster optimization, the k -means algorithm is executed strictly on the four sub-dimensional continuous variables: Housing (H), Food (F), Mobility (M), and Product Disposal (P). Because the Total Sustainable Consumption Index (S^{Total}) is a deterministic aggregate function of these four underlying dimensions, including it directly in the k -means feature space would inflate Euclidean distance metrics and unintentionally double-weight the component variables. Therefore, S^{Total} is excluded from the clustering algorithm's distance calculations.

Once the cluster partitions are established based on the 4-dimensional vector $\mathbf{X}_i = (\mathbf{X}_{i,H}, \mathbf{X}_{i,F}, \mathbf{X}_{i,M}, \mathbf{X}_{i,P})^T$, the aggregate score S^{Total} is re-introduced strictly as an extrinsic descriptive variable for post-hoc profiling, summary statistics, and visual interpretation across the identified macro-tiers.

3.3 Formal Definition of the Multidimensional Profiling Framework

To capture these domain-specific trade-offs without losing interpretable structure, we formulate a two-stage deterministic cross-classification profiling framework.

Stage 1: Global Macro-Segmentation (k -Means Clustering)

In the first phase, households are partitioned into three global macro-tiers based on their overall performance S_i^{Total} . Applying k -means clustering ($k = 3$) to S_i^{Total} partitions the dataset into three distinct global clusters $C_g \in \{\text{Low, Middle, High}\}$:

$$C(S_i^{\text{Total}}) = \begin{cases} 1 \text{ (Low)}, & S_i^{\text{Total}} \in [0.00, 0.33] \\ 2 \text{ (Middle)}, & S_i^{\text{Total}} \in [0.34, 0.66] \\ 3 \text{ (High)}, & S_i^{\text{Total}} \in [0.67, 1.00] \end{cases}$$

Stage 2: Dimensional Discretization and Combo Index Mapping

In the second phase, each of the four underlying continuous dimensional variables $X_{i,d}$ (where $d \in \{1:\text{Housing}, 2:\text{Food}, 3:\text{Mobility}, 4:\text{Disposal}\}$) is discretized into ordinal performance states using an identical three-tier scaling function $\delta(X_{i,d})$:

$$\delta(X_{i,d}) = \begin{cases} 1 \text{ (Low)}, & 0.00 \leq X_{i,d} \leq 0.33 \\ 2 \text{ (Middle)}, & 0.34 \leq X_{i,d} \leq 0.66 \\ 3 \text{ (High)}, & 0.67 \leq X_{i,d} \leq 1.00 \end{cases}$$

For every household i , an N -dimensional concatenated vector—termed the Combo Index ($\mathcal{CJ}_i$)—is constructed:

$$\mathcal{CJ}_i = (\delta(X_{i,1}) - \delta(X_{i,2}) - \delta(X_{i,3}) - \delta(X_{i,4})) \equiv \text{H-F-M-P}$$

Because $d = 4$ dimensions and each dimension possesses $m = 3$ discrete levels, the potential profile space spans $m^d = 3^4 = 81$ unique structural configurations (ranging from 1-1-1-1 to 3-3-3-3).

3.4 Positioning Relative to Model-Based Segmentation (LPA/LCA)

Alternative probabilistic methods—such as Latent Profile Analysis (LPA), Latent Class Analysis (LCA), and Finite Mixture Models (FMM)—identify latent subpopulations using probabilistic density estimations and maximum likelihood parameters. While model-based probabilistic methods excel in identifying unobserved Gaussian sub-distributions, the proposed deterministic multidimensional

cross-classification framework offers distinct operational advantages for empirical sustainability profiling:

- **Deterministic Transparency & Policy Rule-Making:** Unlike LPA/LCA, where class assignment probabilities can shift when new data points are introduced or model covariance structures change, the Combo Index provides absolute, rule-based thresholds. Policy intervention criteria can be directly tied to static profile definitions (e.g., targeting households mapped to *-1-*-* specifically for food-waste initiatives).
- **Granular Nuance vs. Cluster Smoothing:** Conventional mixture models or single-step k -means tend to merge rare or asymmetrical behavioral combinations into larger, averaged components. The 81-profile matrix preserves low-frequency, highly asymmetric configurations (e.g., 3-1-3-1—high housing/mobility, low food/disposal sustainability) that would otherwise be smoothed out by Gaussian mixture centroids.
- **Diagnostic Utility:** By cross-tabulating global k -means macro-clusters (C_g) against the localized Combo Index (C_{I_i}), researchers can audit intra-cluster heterogeneity—directly observing how many households achieving a "High" aggregate score still suffer from "Low" performance in specific behavioural domains.

3.5 Further Explanations

A combo index is calculated. The combo index is in the following format H-F-M-P. H (housing), F (food), M (mobility), P (product disposal). Each letter in the combo index may have the following values: 1 – low, 2 – middle, 3 – high. For example, a combo index “1-1-1-1” means low values in all dimensions. For example, a combo index “2-1-2-1” means People with middle levels of housing and mobility index and low levels in food and product disposal.

This paper introduces an innovative methodology for profiling household sustainable consumption patterns. The framework begins with an initial three-cluster segmentation, followed by sub-segmentation based on primary demographic and behavioural criteria. Data was gathered from a survey of 2,117 households across Varna, Sofia, and Svishtov between 2021 and 2022. Each household's performance was evaluated across five key metrics: an overall score alongside four specific dimensions—housing, food, mobility, and product disposal.

Standard techniques like k -means clustering can identify general activity groups; however, evaluating four distinct consumption pillars generates far more granular profiles. Furthermore, because the overall score is functionally dependent on its individual components, the range of applicable analytical methods is constrained. By categorizing households into high, medium, and low tiers for both the overall score and each individual dimension, this framework uncovers underlying nuances. For example, a high overall score does not automatically imply high performance across all four sub-dimensions. Analysing these sub-level dimensional

combinations provides deeper insights into how specific drivers contribute to the composite sustainability index.

4. Results and Discussion

With $d = 4$ dimensions and $m = 3$ performance tiers per dimension, the theoretical profile space spans $3^4 = 81$ distinct behavioural configurations. In our empirical sample of 2,117 households, 22 out of the 81 theoretical profiles are observed, reflecting diverse behavioural trade-offs across domains. To maintain analytical clarity while ensuring complete empirical transparency, we structure the profile reporting into a two-tiered presentation: 1. Main Text Focus (Dominant Typologies): The main text analyses the core behavioural archetypes—defined as profile configurations representing at least 95% of the sample. Tables 4-6 highlight these dominant profiles. Low-frequency configurations (e.g., households exhibiting high sustainability in housing but low performance in mobility) are not discussed in the text as substantively informative edge cases. These rare profiles highlight niche behavioural trade-offs and structural constraints that warrant targeted policy attention rather than statistical exclusion.

The dataset used for profiling household outcomes across five sustainability indices comprises a total of 10,574 individual index values. For each household, we calculated the following indices: sustainable consumption; housing-related sustainable consumption; sustainable consumption in the domain of food; sustainable mobility within the local area; and waste utilisation and management.

Table 1. Descriptive Statistics for the Dataset

N/Dimensions	Housing index	Food index	Mobility index	Product disposal index	Sustainable consumption index
N (Valid)	2117	2106	2117	2117	2117
N (Missing)	0	11	0	0	0
Range	1.000	1.000	0.889	0.667	0.779
Minimum	0.000	0.000	0.000	0.000	0.029
Maximum	1.000	1.000	0.889	0.667	0.809

Source: Own elaboration.

The quick cluster method is used for clusterization the dataset. Cluster 1 comprises households with low scores on the Sustainable Consumption Index, as well as low values across the remaining four indices. Cluster 2 includes households with moderate scores on the Sustainable Consumption Index, positioned near the lower boundary of the interval for this category. The households grouped within this cluster exhibit average values on the indices related to housing and food consumption, while simultaneously demonstrating low scores on the indices associated with local mobility and product disposal.

In the initial model specification, uniform fixed thresholds were applied across all sub-indices: Low [**0.00, 0.33**], Middle [**0.34, 0.66**], and High [**0.67, 1.00**]. However, empirical evaluation of the component distributions reveals that the continuous indices possess distinct operational ranges and scale ceilings.

As shown in the descriptive statistics (Table 1), the Product Disposal Index (**P**) exhibits an observed empirical maximum of **0.667**, while the Mobility Index (**M**) caps well below **1.00**. Under fixed uniform binning, placing the "High" threshold at ≥ 0.67 renders a "High" classification in Product Disposal mathematically impossible by construction. Consequently, structural zeroes in the 81-profile space would reflect artifacts of the binning scheme rather than actual household behavioural constraints.

To ensure that performance tiers accurately reflect relative behavioural performance within each domain, we recommend replacing fixed global thresholds with dimension-specific empirical quantile cut-offs. For each dimension $d \in \{H, F, M, P\}$, the continuous index $X_{i,d}$ is discretized into three statistically balanced performance tiers based on its empirical distribution across the population:

$$\delta(X_{i,d}) = \begin{cases} 1 \text{ (Low)}, & X_{i,d} \leq Q_{1,d} \\ 2 \text{ (Middle)}, & Q_{1,d} < X_{i,d} \leq Q_{2,d} \\ 3 \text{ (High)}, & X_{i,d} > Q_{2,d} \end{cases}$$

Where:

$Q_{1,d}$ represents the 33.3rd percentile (lower tertile cutoff) for dimension d .

$Q_{2,d}$ represents the 66.7th percentile (upper tertile cutoff) for dimension d .

This approach (implementation of Quantile-Based Dimension-Specific Thresholds) may be implemented in another article.

Cluster 3 also encompasses households with moderate scores on the Sustainable Consumption Index, though situated at the upper boundary of the interval for this category. These households display high values on the Housing Index (at the lower end of the high category) and the Food Index, a moderate score on the Mobility Index, and a low score on the Product Disposal Index.

Table 2. Final Cluster Centers

Dimensions	Cluster 1 (low)	Cluster (middle)	Cluster 3 (high)
Housing index	0.275	0.500	0.669
Food index	0.220	0.494	0.701
Mobility index	0.171	0.243	0.510
Product disposal index	0.142	0.173	0.243
Sustainable consumption index	0.212	0.378	0.544

Source: Own elaboration.

To characterize the contribution of each sustainability dimension to the global cluster solution, an Analysis of Variance (ANOVA) decomposition was conducted across the identified macro-clusters ($k = 3$).

Contrary to conventional hypothesis testing on independently sampled groups, the p -values in a post-hoc k -means ANOVA table cannot be interpreted as standard inferential tests of statistical significance. Because the k -means algorithm explicitly optimizes the distance between cluster centroids to maximize between-group variance relative to within-group variance, low p -values ($p < 0.05$) are a structural artifact of the optimization procedure rather than proof of population validity.

Consequently, the ANOVA output (Table 2) is employed strictly as a descriptive summary. The resulting F -ratios serve solely to rank the relative importance of each sub-dimension in differentiating the clusters—indicating which behavioural domains drive the separation between Low, Middle, and High macro-tier households.

To evaluate the true mathematical quality, compactness, and separation of the $k=3$ cluster solution without relying on p -values, we did standard internal validation metric (Silhouette Width). The stability metrics (ARI and Kappa) demonstrate excellent alignment across sub-samples, confirming that the three-tier macro-segmentation reflects stable, reproducible structures within the target population.

Table 3. Count of Cases in each Cluster

Cluster	Count	Relative share of the cluster in the whole population
1	720	34,2%
2	925	43,9%
3	461	21,9%
Valid	2106	100%
Missing	11	

Source: Own elaboration.

Table 4. Calculation of “Combo Index” (a Fragment from the Dataset)

Case	Housing index	Food index	Mobility index	Product disposal index	Sustainable consumption index	Combo index	Combo index length
1	2	1	1	1	1	2-1-1-1	7
2	1	1	1	1	1	1-1-1-1	7
3	2	1	2	1	1	2-1-2-1	7
4	2	1		1	1	2-1--1	6

Source: Own elaboration.

Values of the indices: 1 – low, 2 – middle, 3 – high

The combo index is calculated in MS Excel with a formula (concatenating the values of the 4 dimensions (H, F, M, P) with small dashes “-”).

=E3&"-"&F3&"-"&G3&"-"&H3

The combo index contains only the dimensions: housing, food, mobility and product disposal. Cases which have a combo index length of 7 (4 indices and 3 dashes) are analysed.

If we had only 3 types of households (with low indices (e.g. 1-1-1-1), middle indices (2-2-2-2) and high indices (3-3-3-3)) the world would be only from 3 categories. Rather than viewing low-frequency profile combinations as statistical noise, our framework recognizes them as reflecting the rich diversity of real-world household constraints and lifestyle trade-offs. Tailored policy interventions require recognizing this spectrum rather than assuming a one-size-fits-all sustainable consumer archetype. As it is seen from the fragment of the database (Table 4), row 1 (case 1) shows a household with low SCI but which is not low in all 4 dimensions. Case 3 shows a household with low SCI but 2 of the dimensions are with low indices and 2 other dimensions are with middle indices.

This visualization tracks how households' transition from their overall macro-tier into specific dimensional performance configurations. It instantly illustrates both the dominant "aligned" pathways (e.g., '1-1-1-1' and '3-3-3-3') and the asymmetric pathways (e.g., '3-2-1-2'), allowing for rapid identification of domain-specific bottlenecks across the entire population.

Table 5. In-depth Clusterisation within Cluster 1 (Having Cluster Centre of the sustainable Consumption index 0.212 – low level)

Combo cluster	Number of cases within cluster 1	Per cent of cases within cluster 1	Interpretation
1-1-1-1	308	43%	People with a low level of the indices in all dimensions.
2-1-1-1	158	22%	People with middle level of housing index and low level in all other dimensions.
1-2-1-1	43	6%	People with a middle level of food index and low level in all other dimensions.
1-1-2-1	17	2%	People with a middle level of mobility index and low level in all other dimensions.
2-1-2-1	10	1%	People with middle levels of housing and mobility index and low levels in food and product disposal.

Source: Own elaboration.

Other combo clusters within cluster 1 cover fewer than 10 cases or less than 1% of the respondents within cluster 1. Cluster 1 identifies two main groups of households – given in the two top rows of Table 5.

Table 6. In-depth Clusterisation within Cluster 2 (Having Cluster Centre of the Sustainable Consumption index 0.378 – middle level)

Combo cluster	Number of cases within cluster 2	Per cent of cases within cluster 2	Interpretation
2-2-1-1	323	35%	Middle levels of the housing and food indices. Low levels of mobility and product disposal indices.
2-2-2-1	92	10%	Middle levels of the housing, food and mobility indices. Low levels of product disposal index.
2-3-1-1	45	5%	Middle level of housing index. High level of food index. Low levels of mobility and disposal indices.
3-2-1-1	32	3%	High level of housing index. Middle level of food index. Low levels of mobility and disposal indices.
1-2-1-1	23	2%	Low level of housing index. Middle level of food index. Low levels of mobility and disposal indices.
2-1-1-1	23	2%	Middle level of housing index. Low levels of food, mobility and disposal indices.
2-2-1-2	23	2%	Middle levels of the housing, food and disposal indices. Low levels of mobility index.
1-2-2-1	18	2%	Low levels of housing and product disposal indices. Middle levels of food and mobility indices.
2-1-2-1	15	2%	Middle levels of housing and mobility indices. Low levels of food and product disposal.

Source: Own elaboration.

Other combo clusters within cluster 2 cover fewer than 10 cases or less than 1% of the respondents within cluster 2. Cluster 2 identifies two main groups of households – given in the two top rows of Table 6.

Table 7. In-depth Clusterisation within Cluster 3 (Having Cluster Centre of the Sustainable Consumption index 0.544 – middle level)

Combo cluster	Number of cases within cluster 3	Per cent of cases within cluster 3	Interpretation
2-2-2-1	89	19%	Middle levels of the housing, food and mobility indices. Low levels of product disposal index.
2-3-2-1	49	11%	Middle level of housing and mobility indices.

Combo cluster	Number of cases within cluster 3	Per cent of cases within cluster 3	Interpretation
			High level of food index. Low level of product disposal index.
3-2-2-1	41	9%	High level of housing index. Middle levels of food and mobility indices. Low level of product disposal index.
3-3-2-1	40	9%	High levels of housing and food indices. Middle level of mobility index. Low level of product disposal index.
3-3-1-1	21	5%	High levels of housing and food indices. Low levels of mobility and product disposal indices.
3-3-2-2	21	5%	High levels of housing and food indices. Middle levels of mobility and product disposal indices.
2-2-2-2	16	3%	Middle levels of housing, food, mobility and product disposal indices.
3-3-3-2	13	3%	High levels of housing, food and mobility indices. Middle level of product disposal index.

Source: Own elaboration.

Other combo clusters within cluster 3 cover fewer than 10 cases or less than 3% of the respondents within cluster 3. Cluster 3 identifies two main groups of households – given in the two top rows of Table 6.

5. Discussion

Evaluating the specific dimensional combinations across high, medium, and low levels of overall sustainable consumption yields crucial analytical insights. The framework proposed here enables an in-depth investigation into the specific drivers required to attain target scores on the composite sustainability index. To support these findings, visual representations are provided, serving as a model for illustrating comparable cluster-based methodologies. Beyond this specific study, the analytical framework is highly adaptable and can be applied to diverse sustainable consumption datasets. Following the interdisciplinary research spiral, subsequent steps involve identifying shared demographic and behavioural traits within the newly established complex categories.

The combo index enables the identification of nuanced patterns in household behaviour across each segment. For instance, Segment 1 reveals a relatively homogeneous behavioural profile (Table 5). Over 40% of households in this segment exhibit exceptionally low scores across all sustainable consumption indices. However, one-fifth of the households demonstrate moderate levels on the housing-related sustainable consumption index, while maintaining low scores on the

remaining indices. A negligible proportion of households show moderate values either on the food-related or mobility-related sustainable consumption indices. Only isolated cases display moderate scores simultaneously on both the housing and mobility indices. These findings suggest potential for differentiated interventions within this segment to promote sustainable consumption.

Across all households in Segment 1, there is a clear need for targeted efforts aimed at fostering understanding and habit formation in relation to sustainable practices concerning food, mobility, and product utilization. For the majority of this segment, additional work is required to address all aspects of housing-related sustainability. In certain cases, it is necessary to identify which specific sustainable behaviours warrant greater attention and tailored support.

Segment 2 presents a broader diversity of composite index configurations (Table 6). For more than one-third of the households in this segment, their level of sustainable consumption is shaped by a combination of moderate scores on the housing and food indices, while the remaining two indices reflect low levels of sustainability. In 10% of households, low sustainability is observed solely in relation to the product disposal index, whereas the other indices—housing, food, and mobility—register moderate levels. A small subset of households (8%) in this segment demonstrate high levels of sustainability on both the housing and food indices. Other composite index configurations appear only in marginal household groups.

Segment 3 is the most fragmented (Table 7). The largest group within this segment, comprising approximately one-fifth of the households, exhibits moderate levels of sustainable consumption across three of the four primary indices: housing, food, and mobility. Product disposal emerges as the weakest dimension of their consumption behaviour. Additionally, 18% of surveyed households show high levels of sustainability either in housing alone or in both housing and food. For the remaining two indices—mobility and product disposal—these households display consistent patterns, with moderate and low levels of sustainability, respectively.

6. Conclusions

The proposed methodology enables a more nuanced identification of behavioural differences among households in relation to sustainable consumption. The delineation of subsegments facilitates informed decision-making regarding the necessity of applying differentiated approaches within a single segment. Empirical data confirm the existence of variations in the combinations of segmentation criteria within the same segment. This, in turn, enables the development of alternative strategies within the segment. The assessment of the effectiveness and efficiency of such differentiated interventions in the management of sustainable consumption remains a subject for future research.

The implementation of the Quantile-Based Dimension-Specific Thresholds approach may be implemented in another article.

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