Step 1: Deciding (not) to Segment

1.1 Implications of Committing to Market Segmentation

Market segmentation, while a valuable marketing strategy, requires a long-term commitment from organizations. It is not a casual endeavor but more akin to a marriage than a date. Commitment to market segmentation demands a willingness to make substantial changes and investments, as highlighted by Cahill (2006). The costs involved, including research, surveys, focus groups, and the development of tailored packages and advertisements, must be justified by the expected increase in sales. The fundamental truism is that segmentation strategy should be more profitable than marketing without it, considering the expenses incurred in its development and implementation. Embarking on market segmentation necessitates potential changes such as product development or modification, adjustments in pricing and distribution channels, and alterations in communication strategies. These changes can impact the internal structure of the organization, leading to a recommendation by Croft (1994) to organize around market segments rather than products to maximize the benefits of segmentation. This entails creating strategic business units aligned with specific segments to ensure a continual focus on evolving segment needs. Given the profound implications of this long-term commitment, the decision to explore market segmentation potential should be a top-level executive decision. Continuous and systematic communication and reinforcement across all organizational levels and units are crucial for the successful adoption and implementation of a market segmentation strategy.

1.2 Implementation Barriers

Implementing market segmentation in organizations encounters multifaceted barriers that necessitate careful consideration. Senior management plays a pivotal role, and a lack of leadership, commitment, and resource allocation can impede meaningful segmentation. Organizational culture, if not market-oriented, poses challenges, requiring a shift towards consumer-centric thinking and effective communication. Insufficient training and expertise, especially in data management and analysis, hinder the understanding of segmentation foundations. Objective restrictions, such as financial limitations or an inability to make necessary structural changes, and process-related issues, like unclear segmentation objectives and inadequate planning, can impede progress. Moreover, operational-level challenges arise when management is hesitant to adopt unfamiliar techniques, emphasizing the need for simplicity and visualized results. Identifying these barriers early on is crucial, and if persistent, careful consideration should be given to whether market segmentation aligns with organizational goals. McDonald and Dunbar stress the importance of resolute dedication, patience, and a proactive approach to navigate challenges during implementation.

Step 2: Specifying the Ideal Target Segment

2.1 Segment Evaluation Criteria

The third layer of market segmentation analysis, depicted in Fig.2.1, heavily relies on continuous user input throughout various stages, emphasizing that involvement extends beyond initial briefing and concluding marketing mix development. In Step 2, the organization's conceptual contribution involves defining two sets of segment evaluation criteria: knock-out criteria, representing essential features for targeting, and attractiveness criteria, assessing the desirability of compliant segments. While literature lacks a clear distinction, proposed criteria (Table 4.1) guide this evaluative process, crucially impacting data collection (Step 3) and segment selection (Step 8).

Table 4.1 Criteria proposed in the literature for the evaluation of market segments in chronological order.

Source	Evaluation criteria
Day (1984)	Measurable, Substantial, Accessible, Sufficiently different, At suitable life-cycle stage
Croft (1994)	Large enough, Growing, Competitively advantageous, Profitable, Likely technological changes, Sensitivity to price, Barriers to entry, Buyer or supplier bargaining power, Socio-political considerations, Cyclicality and seasonality, Life-cycle position
Myers (1996)	Large enough, Distinguishable, Accessible, Compatible with company
Wedel and Kamakura (2000)	Identifiable, Substantial, Accessible, Responsive, Stable, Actionable
Perreault Jr and McCarthy (2002)	Substantial, Operational, Heterogeneous between, Homogeneous within
Lilien and Rangaswamy (2003)	Large enough (market potential, current market penetration), Growing (past growth forecasts of technology change), Competitively advantageous (barriers to entry, barriers to exit, position of competitors), Segment saturation (gaps in marketing), Protectable (patentable products, barriers to entry), Environmentally risky (economic, political, and technological change), Fit (coherence with company's strengths and image), Relationships with other segments (synergy, cost interactions, image transfers, cannibalisation), Profitable (entry costs, margin levels, return on investment)
McDonald and Dunbar (2004)	Segment factors (size, growth rate per year, sensitivity to price, service features and external factors, cyclicality, seasonality, bargaining power of upstream suppliers), Competition (types of competition, degree of concentration, changes in type and mix, entries and exits, changes in share, substitution by new technology, degrees and type of integration), Financial and economic factors (contribution margins, capacity utilisation, leveraging factors, such as experience and economies of scale, barriers to entry, or exit), Technological factors (maturity and volatility, complexity, differentiation, patents and copyrights, manufacturing processes), Socio-political factors (social attitudes and trends, laws and government agency regulations, influence with pressure groups and government representatives, human factors, such as unionisation and community acceptance)
Dibb and Simkin (2008)	Homogeneous, Large enough, Profitable, Stable, Accessible, Compatible, Actionable
Sternthal and Tybout (2001)	Influence of company's current position in the market on growth opportunities, Competitor's ability and motivation to retaliate, Competence and resources, Segments that will prefer the value that can be created by the firm over current market offerings, Consumer motivation and goals indicating gaps in marketplace offerings when launching a new company
West et al. (2010)	Large enough, Sufficient purchasing power, Characteristics of the segment, Reachable, Able to serve segment effectively, Distinct, Targetable with marketing programs
Solomon et al. (2011)	Differentiable, Measurable, Substantial, Accessible, Actionable

2.2 Knock-Out Criteria

Knock-out Criteria in Market Segmentation:

1. Substantiality, Measurability, and Accessibility: Suggested by Kotler (1994), Initial criteria to assess segment qualification.

2. Homogeneous Segment: Members within the segment must share similarities.

3. Distinctiveness: Segment members must be distinctly different from those in other segments.

4. Adequate Size: The segment should be large enough to justify customizing the marketing mix.

5. Alignment with Organizational Strengths: The segment must match the capabilities of the organization.

6. Identifiability: Members of the segment should be identifiable in the marketplace

7. Reachability: A means to connect with segment members for accessible marketing.

8. Understanding and Specification: Senior management, segmentation team, and advisory committee should comprehend and, if needed, specify criteria details.

2.3 Attractiveness Criteria

In addition to the knock-out criteria, Table 4.1 also lists a wide range of segment attractiveness criteria available to the segmentation team to consider when deciding which attractiveness criteria are most useful to their specific situation. Attractiveness criteria are not binary in nature. Segments are not assessed as either complying or not complying with attractiveness criteria. Rather, each market segment is rated; it can be more or less attractive with respect to a specific criterion. The attractiveness across all criteria determines whether a market segment is selected as a target segment in Step 8 of market segmentation analysis.

2.4 Implementing a Structured Process

In the context of market segmentation, a structured process is widely acknowledged as beneficial, according to leading experts such as Lilien and Rangaswamy (2003) and McDonald and Dunbar (2012). One prevalent method for systematic evaluation of market segments involves using a segment evaluation plot, assessing segment attractiveness against organizational competitiveness. Values on both axes are determined by the segmentation team, emphasizing the absence of a universally applicable set of criteria. Selecting criteria involves negotiation and agreement, with McDonald and Dunbar (2012) recommending no more than six factors. Input from a diverse team is optimal, with a core team proposing an initial solution for discussion and potential modification by an advisory committee. The inclusion of diverse organizational perspectives is essential, given that each unit brings a distinct viewpoint to the deliberations. While the completion of the segment evaluation plot occurs later in the process, laying the groundwork for selecting attractiveness criteria early on proves advantageous. In Step 2, the team finalizes a list of approximately six attractiveness criteria, each assigned a weight reflecting its importance relative to others.

Step 3: Collecting Data

3.1 Segmentation Variables

Empirical data plays a foundational role in both commonsense and data-driven market segmentation, serving to identify and describe market segments. In commonsense segmentation, a single characteristic, termed the segmentation variable, is used to split the sample into segments. For instance, Table 5.1 illustrates a commonsense segmentation using gender, resulting in distinct segments for men and women. Descriptor variables, encompassing additional personal characteristics, then describe these segments in detail. These descriptors are crucial for effective marketing mix development. In contrast, data-driven segmentation relies on multiple variables to identify or create segments, as demonstrated in Table 5.2. This approach aims to uncover naturally existing or artificially created segments, offering a more intricate understanding of consumer behavior and preferences for targeted marketing strategies.

Table 3.1 Genderasapossiblesegmentationvariableincommonsensemarketsegmentation

Sociodemographics		Travel behaviour	Benefits sought				
gender	age	N° of vacations	relaxation	action	culture	explore	meet people
Female	34	2	1	0	1	0	1
Female	55	3	1	0	1	0	1
Female	68	1	0	1	1	0	0
Female	34	1	0	0	1	0	0
Female	22	0	1	0	1	1	1
Female	31	3	1	0	1	1	1
Male	87	2	1	0	1	0	1
Male	55	4	0	1	0	1	1
Male	43	0	0	1	0	1	0
Male	23	0	0	1	1	0	1
Male	19	3	0	1	1	0	1
Male	64	4	0	0	0	0	0
segmentation variable	descriptor variables						

Table5.2 Segmentation variables in data-driven market segmentation

Sociodemographics		Travel behaviour	Benefits sought				
gender	age	Nº of vacations	relaxation	action	culture	explore	meet people
Female	34	2	1	0	1	0	1
Female	55	3	1	0	1	0	1
Male	87	2	1	0	1	0	1
Female	68	1	0	1	1	0	0
Female	34	1	0	0	1	0	0
Female	22	0	1	0	1	1	1
Female	31	3	1	0	1	1	1
Male	55	4	0	1	0	1	1
Male	43	0	0	1	0	1	0
Male	23	0	0	1	1	0	1
Male	19	3	0	1	1	0	1
Male	64	4	0	0	0	0	0
descriptor variables			segmentation variables				

3.2 Segmentation Criteria

Market segmentation involves making critical decisions even before data collection begins. The choice of segmentation criterion, broader than the segmentation variable, necessitates market knowledge. Common criteria include geographic, socio-demographic, psychographic, and behavioral factors. Geographic segmentation relies on consumer location, simplifying communication targeting. Socio-demographic criteria encompass age, gender, income, and education, while psychographic segmentation explores psychological aspects such as beliefs and lifestyle. Behavioral segmentation, based on actual behavior, captures consumer similarities in purchase patterns. Each criterion has advantages and disadvantages, emphasizing the importance of selecting the simplest and most effective approach tailored to the specific market context.

1. Geographic Segmentation:

Geographic segmentation, the original approach, categorizes consumers based on their location of residence. While effective for targeting specific regions and simplifying communication, it may overlook other crucial characteristics influencing consumer behavior.

2. Socio-Demographic Segmentation:

This method involves using criteria such as age, gender, income, and education to categorize consumers. While providing easily determinable segment memberships, socio-demographic factors may not always explain product preferences or offer sufficient insights for optimal segmentation decisions.

3. Psychographic Segmentation:

Psychographic segmentation groups consumers based on psychological criteria like beliefs, interests, and benefits sought. This approach reflects underlying reasons for consumer behavior but introduces complexity in determining segment memberships. It heavily relies on the reliability and validity of measures used.

4. Behavioral Segmentation:

Behavioral segmentation directly considers similarities in reported or observed behavior, such as prior experience, frequency of purchase, and spending habits. This approach utilizes the very behavior of interest for segment extraction, offering a powerful basis for understanding consumer preferences. Availability of behavioral data, however, can be a challenge.

General Considerations: The selection of a segmentation criterion is a crucial decision that requires prior market knowledge. Few guidelines exist for determining the most appropriate base, emphasizing the importance of choosing the simplest and most effective approach tailored to the specific market context. The advantages and disadvantages of each criterion highlight the need for a thoughtful and context-specific decision-making process.

5.3 Data from Survey Studies:

1. Choice of Variables:

Selecting appropriate variables is crucial for the quality of market segmentation solutions. In data-driven segmentation, including all relevant variables while avoiding unnecessary ones is essential. Unnecessary variables can lead to respondent fatigue, lower response quality, and complicate segmentation analysis.

2. Response Options:

The options provided to respondents impact subsequent analyses. Binary or metric response options are preferred for segmentation analysis due to their compatibility with distance measures. Ordinal data, generated by commonly used response formats, presents challenges in applying standard distance measures.

3. Response Styles:

Survey data is susceptible to biases, including response styles. Response biases, like acquiescence (consistent agreement), can impact segmentation results. Minimizing the risk of capturing response styles during data collection is crucial, and additional analyses may be needed to address biases if attractive market segments emerge.

4. Sample Size:

Sample size significantly influences segmentation analysis. Insufficient samples make it challenging to determine the correct number of market segments. Recommended sample sizes vary, with suggestions of at least 60-70 times the number of segmentation variables. Larger sample sizes consistently improve the correctness of extracted segments.

Key Considerations:

- Sample size of at least 100 respondents per segmentation variable is recommended.

- High-quality, unbiased data is crucial for accurate market segmentation.

- Ideal data should include necessary items, exclude unnecessary or correlated items, be binary or metric, free of response styles, and suitable for the segmentation study's aim.

These considerations emphasize the importance of thoughtful survey design, variable selection, and ensuring adequate sample sizes for robust market segmentation analyses.

3.4 Data from Internal Sources

Organizations increasingly utilize internal data, such as scanner data in grocery stores, airline booking information, and online purchase records, for market segmentation analysis. The strength of this data lies in its representation of actual consumer behavior rather than self-reported intentions, reducing biases associated with imperfect memory and response styles. These automatically generated data require no additional effort for collection if stored in an accessible format. However, a potential drawback is the risk of systematic bias, as the data may primarily reflect existing customers, lacking insights into potential customers with distinct consumption patterns that the organization aims to attract in the future.

3.5 Data from Experimental Studies

Experimental data, derived from field or laboratory experiments, constitutes another valuable source for market segmentation analysis. This data can originate from various experiments, such as assessing consumer responses to advertisements or conducting choice experiments and conjoint analyses. In choice experiments, consumers express preferences among products characterized by specific attribute levels, providing insights into the impact of each attribute and level on consumer choice. This experimental data, offering a controlled environment, enables the identification of segmentation criteria based on consumer reactions to stimuli, providing valuable information for market segmentation analysis.

STEP 6: Profiling Segments

6.1 Identifying Key Characteristics of Market Segments

Identifying key characteristics of market segments is crucial for effective market segmentation, especially in data-driven approaches. Profiling, the sixth step in the process, becomes essential to understand and define the resulting segments. Unlike commonsense segmentation, where predefined profiles exist, data-driven segmentation requires analysis to uncover defining characteristics. Profiling involves characterizing segments individually and in comparison to others, aiming to reveal the unique features that differentiate them. This step is particularly vital when dealing with unconventional or constructed segments. Good profiling forms the basis for accurate interpretation of segmentation results, a critical factor in making strategic marketing decisions. However, data-driven solutions are challenging to interpret, as evidenced by the difficulties reported by marketing managers. Graphical statistical approaches are recommended for profiling, as they make the process less tedious and reduce the risk of misinterpretation. This contrasts with traditional methods that may present results in a confusing or contradictory manner, often lacking clarity in executive summaries and containing insufficiently conclusive information. Overall, effective profiling is essential for unlocking meaningful insights from market segmentation data.

6.2 Traditional Approaches to Profiling Market Segments

We use the Australian vacation motives data set. Segments were extracted from this data set using the neural gas clustering algorithm with number of segments varied from 3 to 8 and with 20 random restarts.

```
R> library("flexclust")

R> data("vacmot", package = "flexclust")

R> load("vacmot-clusters.RData")
```

The passage discusses the challenges in presenting data-driven segmentation solutions to users and managers. Two common presentation formats are highlighted: high-level summaries that oversimplify segment characteristics and large tables providing exact percentages for each segmentation variable, making interpretation difficult. Table 8.1 is used as an example, demonstrating the complexity of comparing segment characteristics.

In Table 8.1, mean values represent percentages of segment members engaged in specific travel motives. Profiling segments requires comparing these percentages across motives and segments, making it a cumbersome task. Defining characteristics of a segment, such as segment 2's motivation for relaxation and budget consciousness, become apparent through these comparisons. Segment 1 is suggested to be a response style segment due to consistently low percentages across travel motives.

The sheer number of comparisons needed for six segments and multiple travel motives is emphasized. For a table with 20 rows, 420 comparisons are required between segments and the total, and an additional 2100 comparisons for five alternative segmentation solutions. Providing information on statistical significance is deemed statistically incorrect due to the creation of maximally different segments that do not permit standard statistical tests. Overall, the passage underscores the complexity and challenges in accurately interpreting and comparing data-driven segmentation results, particularly when presented in tabular form.

Table 8.1 Six segments computed with the neural gas algorithm for the Australian travel motives data set. All numbers are percentages of people in the segment or in the total sample agreeing to the motives

	Seg. 1	Seg. 2	Seg. 3	Seg. 4	Seg. 5	Seg. 6	Total
Rest and relax	83	96	89	82	98	96	90
Change of surroundings	27	82	73	82	87	77	67
Fun and entertainment	7	71	81	60	95	37	53
Free-and-easy-going	12	65	58	45	87	75	52
Not exceed planned budget	23	100	2	49	84	73	51
Life style of the local people	9	29	30	90	75	80	46
Good company	14	59	40	58	77	55	46
Excitement, a challenge	9	17	39	57	76	36	33
Maintain unspoilt surroundings	9	10	16	7	67	95	30
Cultural offers	4	2	5	96	62	38	28
Luxury / be spoilt	19	24	39	13	89	6	28
Unspoilt nature/natural landscape	10	10	13	15	69	64	26
Intense experience of nature	6	8	9	21	50	58	22
Cosiness/familiar atmosphere	11	24	12	7	49	25	19
Entertainment facilities	5	25	30	14	53	6	19
Not care about prices	8	7	43	19	29	10	18
Everything organised	7	21	15	12	46	9	16
Do sports	8	12	13	10	46	7	14
Health and beauty	5	8	10	8	49	16	12
Realise creativity	2	2	3	8	29	14	8

6.3 Segment Profiling with Visualisations

The passage emphasizes the limited use of graphics in presenting market segmentation solutions, despite their importance in statistical data analysis. Graphics, recommended by experts like Tufte and Cleveland, play a crucial role in exploratory statistical analysis, providing insights into complex variable relationships. In times of big data, visualization offers a simple way to monitor developments over time. Recommendations from McDonald, Dunbar, Lilien, and Rangaswamy underscore the value of visualization techniques in interpreting market segmentation analysis results. Presenting information in tabular form is less insightful compared to graphical representation, as noted by Haley. Cornelius et al. recommend a single two-dimensional graphical format for interpreting market structure analysis results. A review of visualisation techniques for cluster analysis and mixture models by Leisch is referenced. Examples of prior visualisations in segmentation solutions are cited from various studies. Visualisations are deemed useful in the data-driven segmentation process for inspecting segments in detail, facilitating the interpretation of segment profiles, and aiding in the selection of the most appropriate segmentation solution among many alternatives. Overall, the passage underscores the significance of incorporating graphics for effective segment profiling in market segmentation analysis.

6.3.1 Identifying Defining Characteristics of Market Segments

A good way to understand the defining characteristics of each segment is to produce a segment profile plot. The segment profile plot shows – for all segmentation variables – how each market segment differs from the overall sample. The segment profile plot is the direct visual translation of tables such as Table 8.1. We can achieve this by clustering the columns of the data matrix:

```
R> vacmot.vdist <- dist(t(vacmot))

R> vacmot.vclust <- hclust(vacmot.vdist, "ward.D2")
```

The t() around the data matrix vacmot transposes the matrix such that distances between columns rather than rows are computed. Next, hierarchical clustering of the variables is conducted using Ward's method. Tourists who care about an unspoilt natural landscape also show interest in maintaining unspoilt surroundings, and seek an intense experience of nature. A segment profile plot like the one in Fig. 6.2 results from:

```
R> barchart(vacmot.k6, shade = TRUE,

+ which = rev(vacmot.vclust$order))
```

This session discusses a visual approach, specifically the segment profile plot, for identifying defining characteristics of market segments, contrasting it with traditional tabular presentation. The segment profile plot organizes variables based on hierarchical clustering, using marker variables highlighted in color for segment distinctiveness. Marker variables deviate by more than 0.25 from the overall mean, or 50% from binary variable means. Empirically determined deviation figures help define substantial differences. The plot displays cluster centers for each segment, making it easier to interpret and compare values with the overall dataset mean. The graphical representation enhances the understanding of defining characteristics, such as budget-consciousness in segment 2 or cultural interest in segment 4. Segments 1 and 5 may represent response style segments, requiring careful interpretation. An eye-tracking study indicates that segment profile plots are quicker to interpret compared to traditional tables, as shown in Fig. 6.3. Longer looking times and more cognitive effort are associated with table interpretation, while the segment profile plot requires less effort to extract information. The passage highlights the value of well-designed graphical visualizations in facilitating managers' interpretation of segmentation results for making long-term strategic decisions, emphasizing the substantial return on investment in employing effective visualizations.

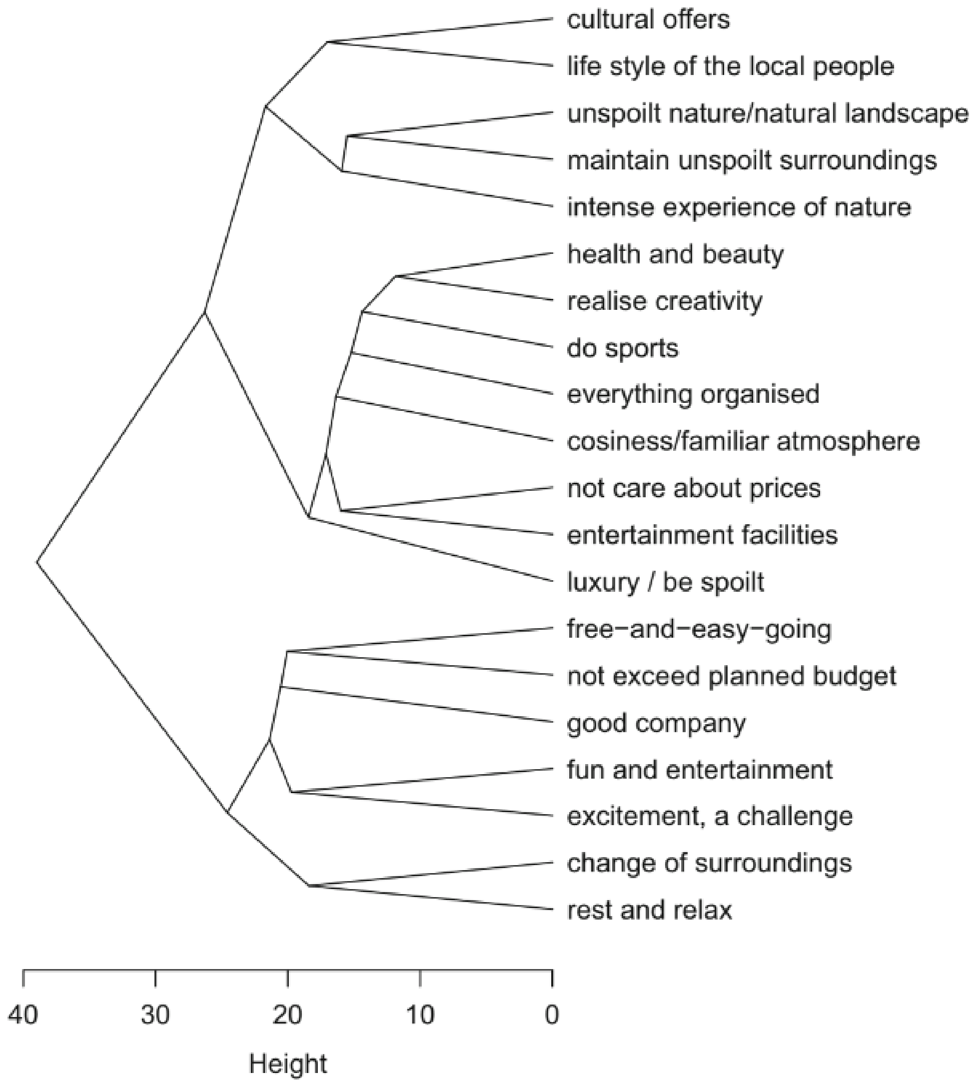

Fig. 6.1 Hierarchical clustering of the segmentation variables of the Australian travel motives data set using Ward's method.

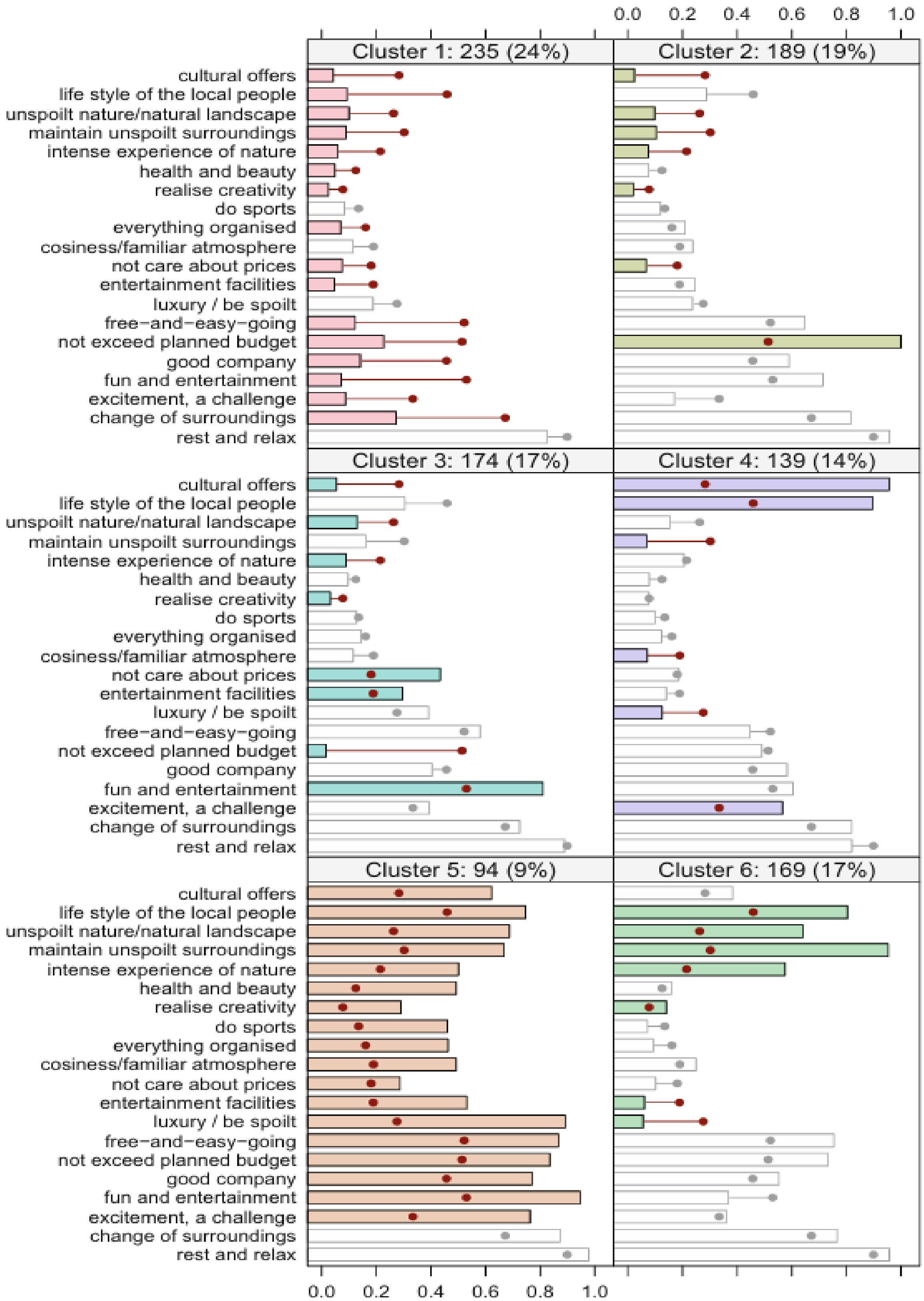

Fig. 6.2 Segment profile plot for the six-segment solution of the Australian travel motives data set

6.3.2 Assessing Segment Separation

The passage introduces the concept of segment separation plots for visualizing segment overlap in market segmentation solutions. These plots are considered straightforward for datasets with a low number of segmentation variables but can become complex as the dimensionality increases. The examples in Fig. 8.4 illustrate segment separation plots for two artificial datasets, highlighting their utility in providing a quick overview of the data and segmentation solution. When dealing with two-dimensional data, no projection is necessary, as demonstrated in the scatter plots in the top row of Fig. 8.4. The color of observations indicates true segment membership, while dashed and solid cluster hulls represent the shape and spread of true segments. Neighbourhood graphs connect segment centers, indicating similarity. Fig. 8.4 provides insights into segment separation in datasets with distinct segments and elliptic data structures.

The passage emphasizes the need for projection techniques when dealing with high-dimensional data. Principal components analysis (PCA) is introduced as one such method, allowing the projection of a 20-dimensional travel motives dataset onto a lower-dimensional space. The code for performing PCA and creating a segment separation plot using the resulting projection is provided:

```
> vacmot.pca <- prcomp(vacmot)

> plot(vacmot.k6, project = vacmot.pca, which = 2:3, xlab = "principal component 2", ylab = "principal component 3")

> projAxes(vacmot.pca, which = 2:3)
```

The resulting plot (Fig. 8.5) is described as messy due to segment overlap, prompting modifications for improved clarity. The code below adjusts colors, omits observations, and highlights the inner area of each segment:

```
> plot(vacmot.k6, project = vacmot.pca, which = 2:3, col = flxColors(1:6, "light"), points = FALSE, hull.args = list(density = 10), xlab = "principal component 2", ylab = "principal component 3")

> projAxes(vacmot.pca, which = 2:3, col = "darkblue", cex = 1.2)
```

The resulting plot (Fig. 8.6) is acknowledged as challenging to interpret due to the absence of natural market segments in the data. Despite this difficulty, the plot highlights distinct characteristics of certain segments based on their preferences, such as a focus on unspoilt surroundings or a preference for luxury and entertainment.

In conclusion, this session underscores the significance of segment separation plots as a visual tool for understanding the overlap between segments in market segmentation solutions, especially in higher-dimensional datasets. The provided examples and code snippets illustrate the practical application of these plots in data analysis.

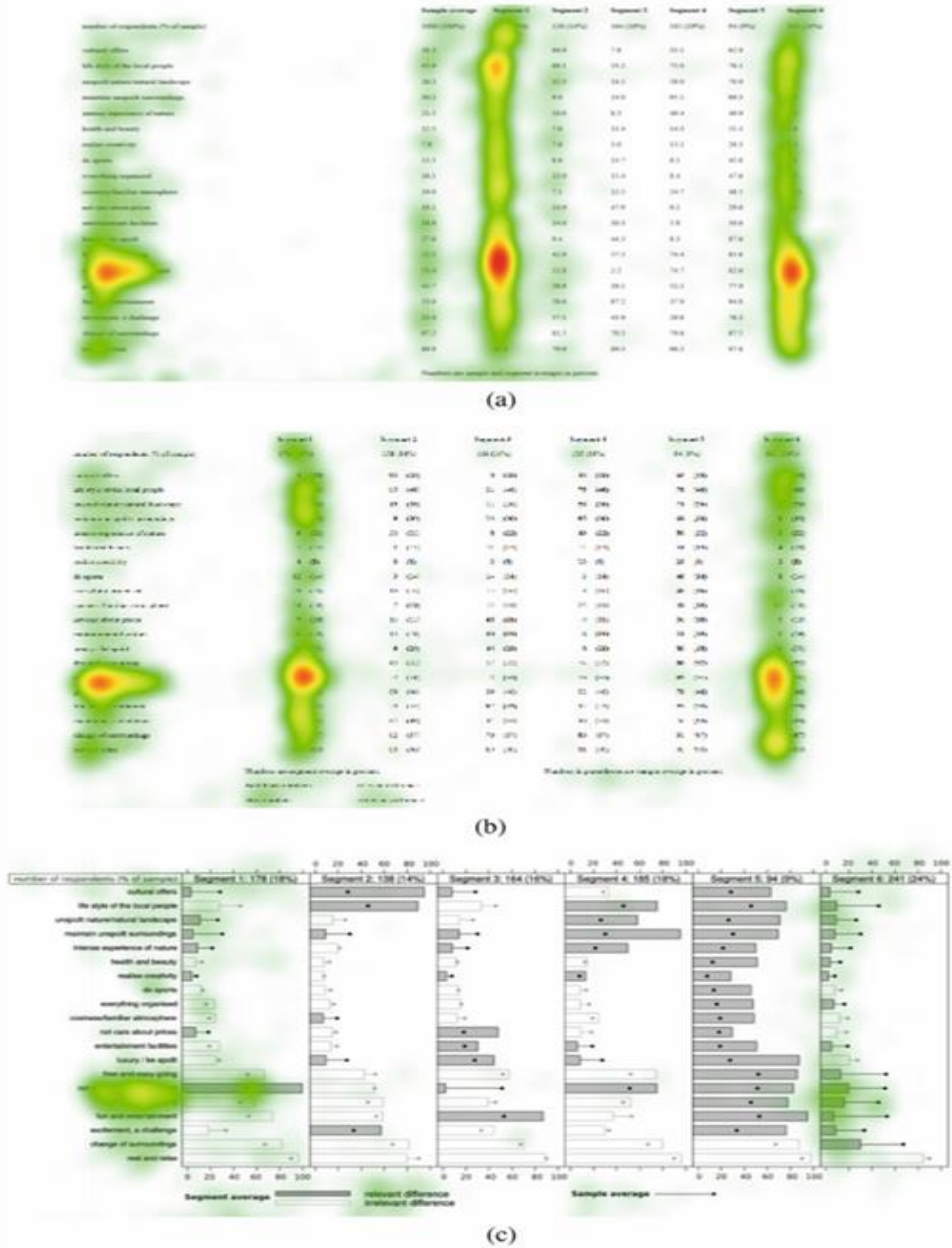

Fig. 8.3 One person's eye tracking heat maps for three alternative ways of presenting segmentation results. (a) Traditional table. (b) Improved table. (c) Segment profile plot

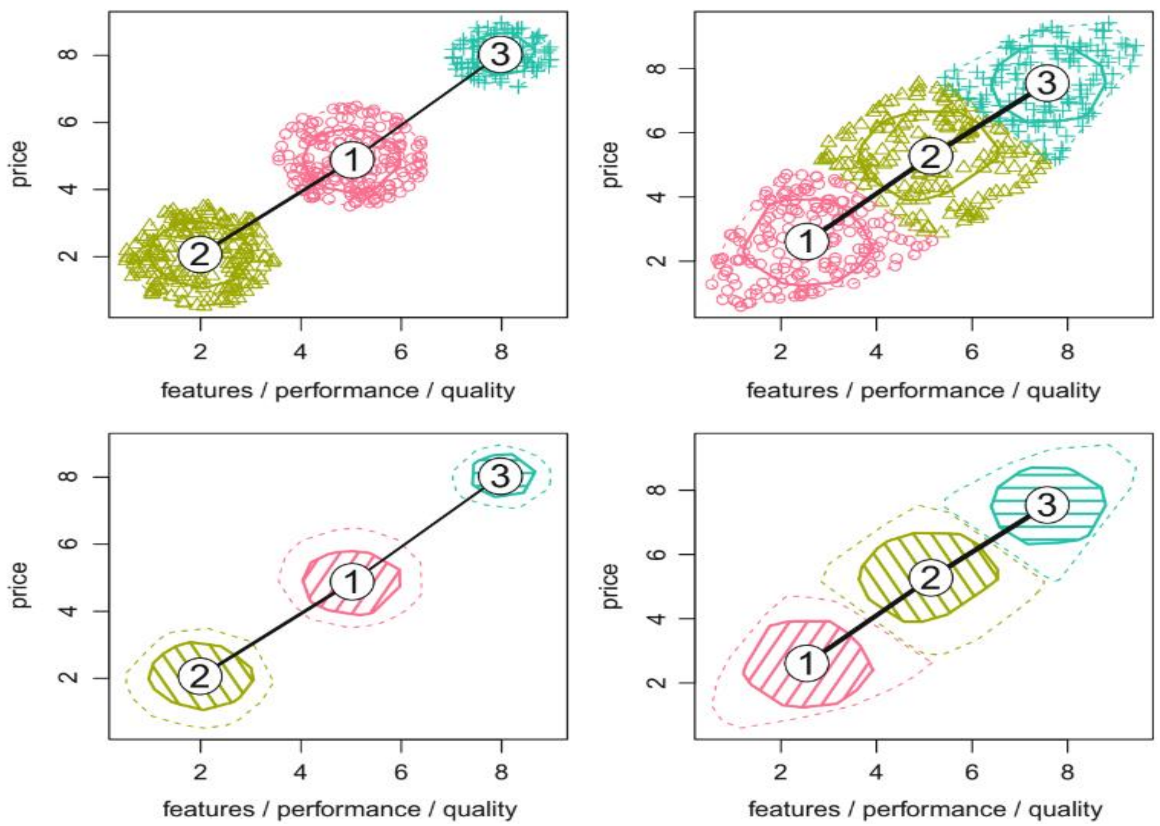

Fig. 6.4 Segment separation plot including observations (first row) and not including observations (second row) for two artificial data sets: three natural, well-separated clusters (left column); one elliptic cluster (right column)

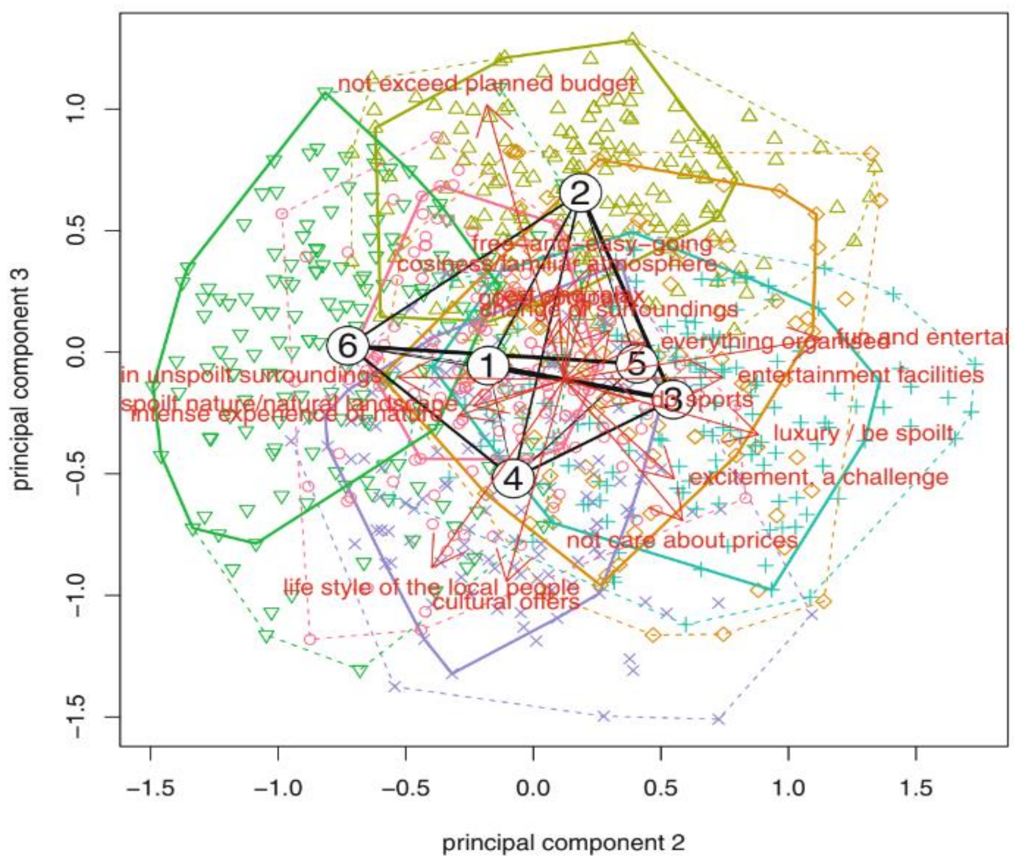

Fig. 6.5 Segment separation plot using principal components 2 and 3 for the Australian travel motives data set

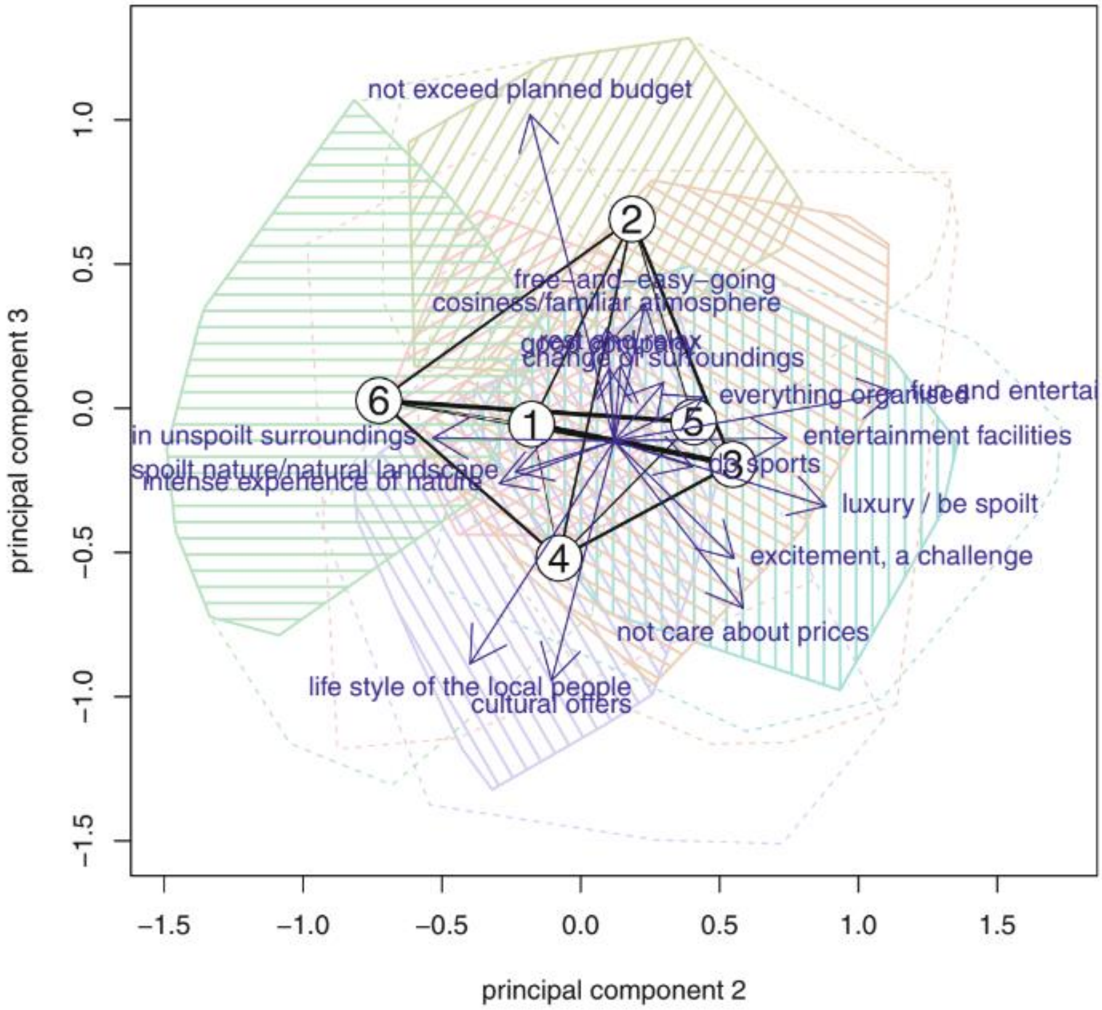

Fig. 6.6 Segment separation plot using principal components 2 and 3 for the Australian travel motives data set without observations.

Step 7: Describing Segments

7.1 Developing a Complete Picture of Market Segments

This session discusses the importance of segment profiling and description in the market segmentation analysis process. Segmentation variables, chosen early in the analysis, are crucial for extracting market segments from empirical data. Step 7, similar to profiling, involves describing market segments using additional information about segment members, referred to as descriptor variables. This step helps gain detailed insights into segment nature and is essential for developing a customized marketing mix.

The analogy of segment profiling and description to dating is used, highlighting the need to get to know potential market segments thoroughly. Profiling involves investigating differences in segmentation variables, while describing segments includes crossing them with various other variables like psychographic, demographic, and socio-economic factors. The paragraph emphasizes the significance of good segment descriptions for developing a targeted marketing strategy. Using the example of a data-driven market segmentation analysis with the Australian travel motives dataset, the paragraph distinguishes between profiling (examining differences in travel motives) and segment description (utilizing additional information like age, gender, past travel behavior). Descriptor variables play a crucial role in segment description, offering insights that contribute to a customized marketing approach.

It also mentions two ways to study differences between market segments with respect to descriptor variables: using descriptive statistics with visualizations or employing inferential statistics. While the traditional marketing literature relies on statistical testing and tabular presentations, visualizations are noted to make segment description more user-friendly. Overall, the paragraph underscores the importance of thorough segment profiling and description for effective market segmentation analysis and strategy development.

7.2 Using Visualisations to Describe Market Segments

A wide range of charts exist for the visualisation of differences in descriptor variables. Here, we discuss two basic approaches suitable for nominal and ordinal descriptor variables (such as gender, level of education, country of origin), or metric descriptor variables (such as age, number of nights at the tourist destinations, money spent on accommodation).

7.2.1 Nominal and Ordinal Descriptor Variables

Australian travel motives data set (see Appendix C.4), data frame vacmotdesc contains several descriptor variables. These descriptor variables are automatically loaded with the Australian travel motives data set. To describe market segments, we need the segment membership for all respondents. We store segment membership in helper variable C6:

R> C6 <- clusters(vacmot.k6)

The sizes of the market segments are

R> table(C6)

C6

123456

235 189 174 139 94 169

The easiest approach to generating a cross-tabulation is to add segment membership as a categorical variable to the data frame of descriptor variables. Then we can use the formula interface of R for testing or plotting:

R> vacmotdesc$C6 <- as.factor(C6)

The following R command gives the number of females and males across market segments:

R> C6.Gender <- with(vacmotdesc,

+ table("Segment number" = C6, Gender))

R> C6.Gender

Gender

Segment number Male Female

1 125 110

2 86 103

3 94 80

4 78 61

5 47 47

6 82 87

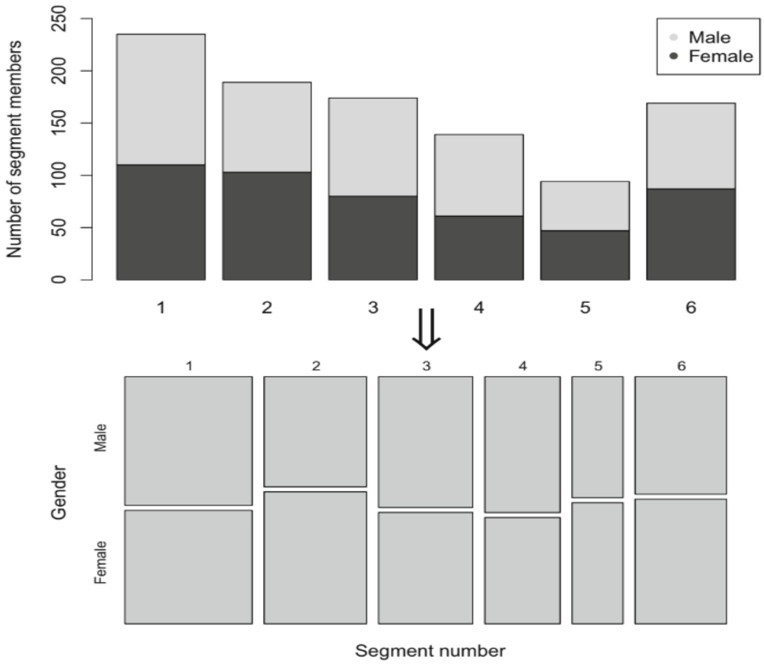

Fig. 7.1 Comparison of a stacked bar chart and a mosaic plot for the cross-tabulation of segment membership and gender for the Australian travel motives data set

Various visualizations and statistical tests used to describe differences between market segments based on nominal or ordinal descriptor variables. The primary visualization method discussed is mosaic plots, which depict cross-tabulations of segment membership with descriptor variables. Figure 7.1 illustrates a mosaic plot showing gender distribution across segments. The height of the rectangles represents the proportion of men or women in each segment, while the width represents the segment sizes. The passage explains that colors in mosaic plots can highlight differences between observed and expected frequencies, with negative differences in red and positive differences in blue, indicating statistical significance. In Figure 7.2, all cells are white, suggesting that the gender distribution across segments is not significantly different. The passage further explains that dashed and solid borders of the rectangles indicate lower or higher than expected frequencies, respectively, but white rectangles signify statistically insignificant differences. Moving on to Figure 7.3, the association between segment membership and income is explored. The mosaic plot shows moderate association, with income categories ranging from lowest to highest. The passage describes how different segments correspond to income categories, revealing insights such as segment 4 containing fewer high-income members and segment 6 having fewer very high-income members. Figure 7.4 depicts the association between segment membership and stated moral obligation to protect the environment. Segment 3, seeking entertainment, has significantly more members with low stated moral obligation, while segment 6, motivated by nature, has a higher proportion of members with high moral obligation. Overall, the passage demonstrates the utility of mosaic plots in visualizing differences between market segments based on descriptor variables, such as gender, income, and moral obligation, providing valuable insights for targeted marketing strategies.

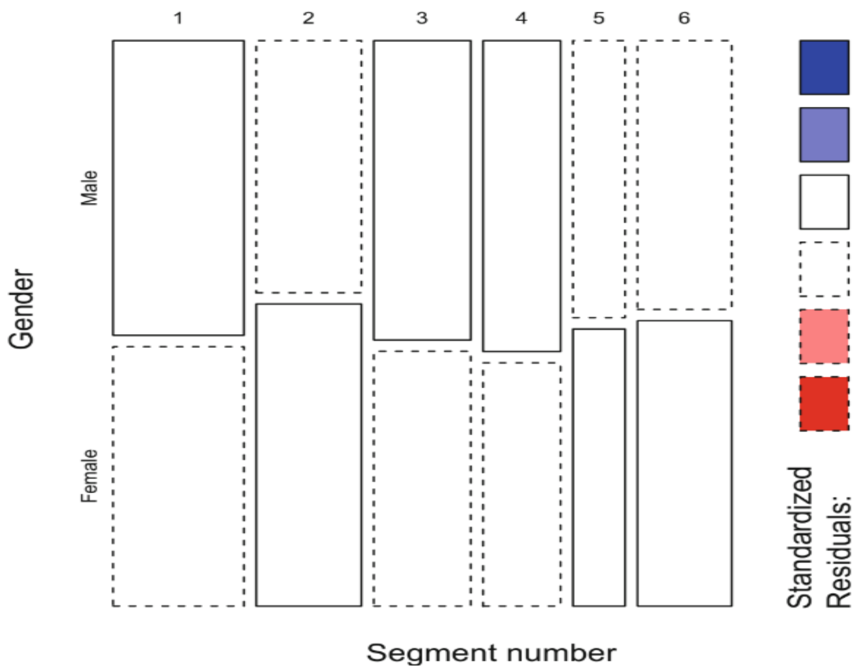

Figure 7.2

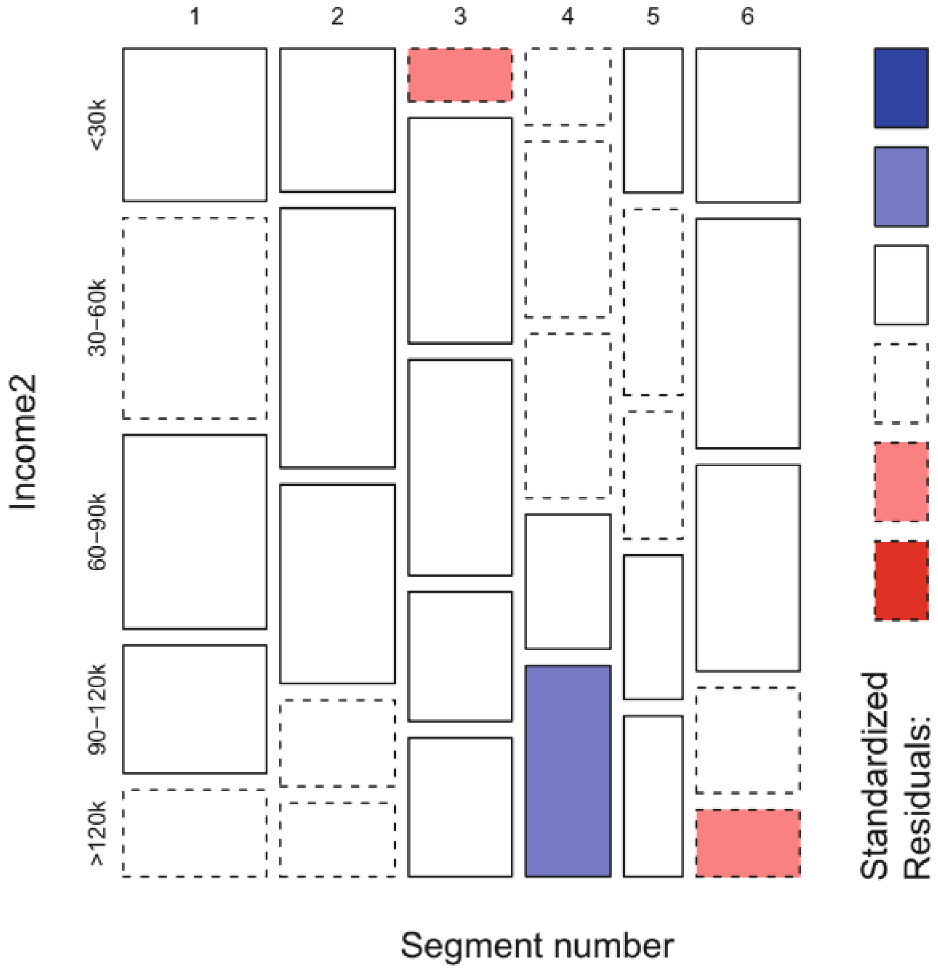

Figure 7.3

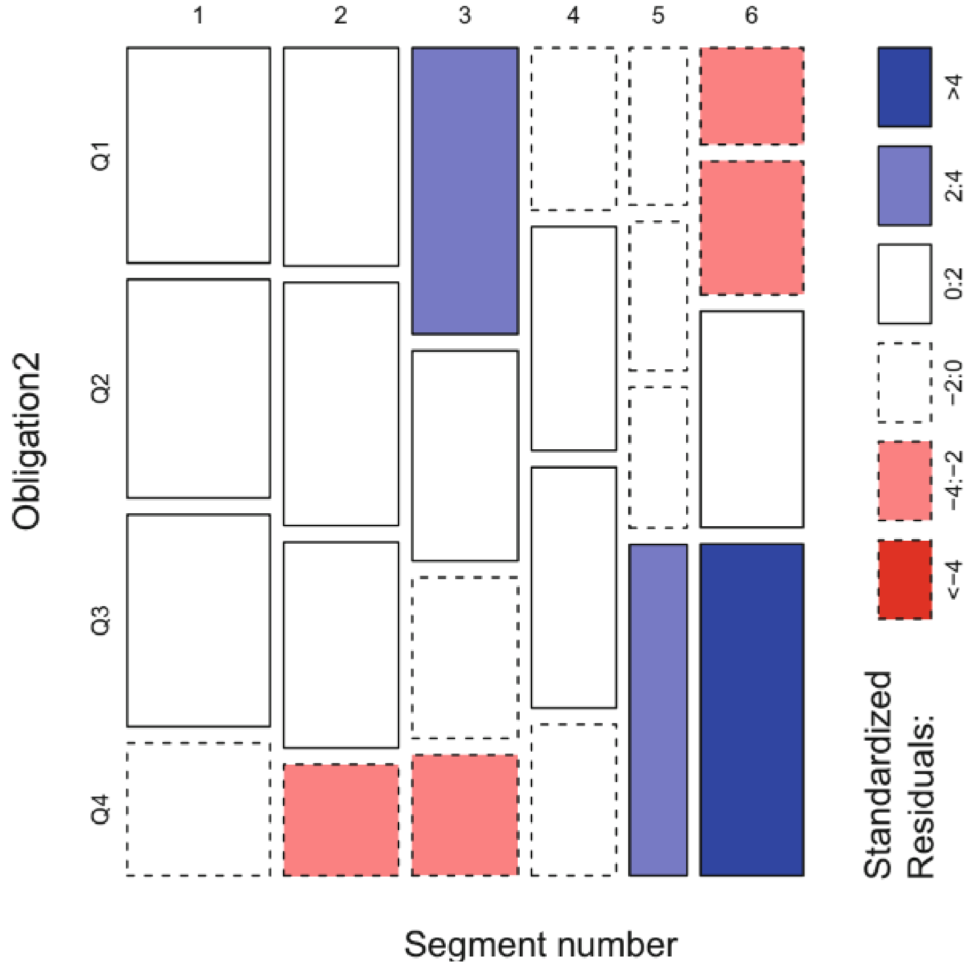

Figure 7.4

7.2.2 Metric Descriptor Variables

The R package lattice (Sarkar 2008) is a valuable tool for generating conditional plots, which are particularly useful for visualizing differences in market segments based on metric descriptor variables. These plots are divided into sections or panels, with each section presenting results for a specific subset of the data, such as different market segments. For instance, the segment profile plot in Section 8.3.1 was created using the lattice package. To illustrate, we can use conditional histograms to compare the age distribution and moral obligation scores across various segments. The following R code generates histograms for age and moral obligation:

library("lattice")

histogram(~ Age | factor(paste("Segment", C6)), data = vacmotdesc, as.table = TRUE)

histogram(~ Obligation | factor(paste("Segment", C6)), data = vacmotdesc, as.table = TRUE)

Figures 9.5 and 9.6 present the resulting histograms, offering an initial glimpse into potential differences between market segments. However, interpreting these differences solely from the plots might prove challenging. To delve deeper into the analysis, parallel box-and-whisker plots are created for both age and moral obligation across different segments. The R code for generating the parallel boxplot for age is as follows:

bo*xplot(Age ~ C6, data = vacmotdesc, xlab = "Segment number", ylab = "Age")*

Figure 9.7 visualizes the distribution of age across segments, showcasing minor differences in median age. To extend the analysis to moral obligation, a modified version of the parallel box-and-whisker plot is employed:

boxplot(Obligation ~ C6, data = vacmotdesc, varwidth = TRUE, notch = TRUE, xlab = "Segment number", ylab = "Moral obligation")

Figure 9.8 incorporates notches representing 95% confidence intervals for median differences, aiding in the interpretation of statistical significance. The plot highlights variations in moral obligation across segments, providing a deeper understanding of the descriptor variable's distribution.

For a more dynamic exploration of descriptor variables across multiple segmentation solutions, a segment level stability across solutions (SLSA) plot can be utilized. This modified version incorporates color-coded nodes to represent moral obligation scores, providing a nuanced view of how this variable evolves across different segmentation solutions:

slsaplot(vacmot.k38, nodecol = vacmotdesc$Obligation)

Figure 9.9 visually presents the mean moral obligation to protect the environment for each segment using distinctive colors. A deep red color indicates high moral obligation, while a light grey color suggests lower moral obligation. The consistent representation of nature-loving tourists along the bottom row implies stability in this potentially attractive market segment across various segmentation solutions.

In summary, the lattice package in R facilitates the creation of informative conditional plots, such as histograms and box-and-whisker plots, allowing for a comprehensive exploration of metric descriptor variables across different market segments. These visualizations provide valuable insights into segment characteristics, aiding marketers and analysts in understanding the nuances of customer behavior.

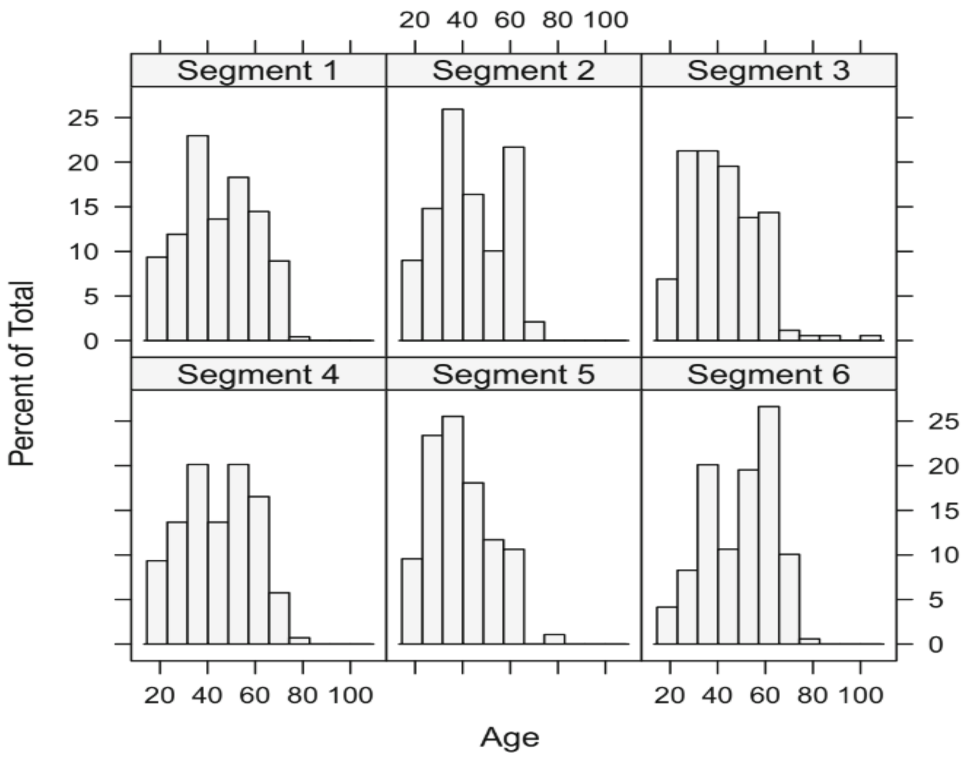

Fig. 7.5 Histograms of age by segment for the Australian travel motives data set

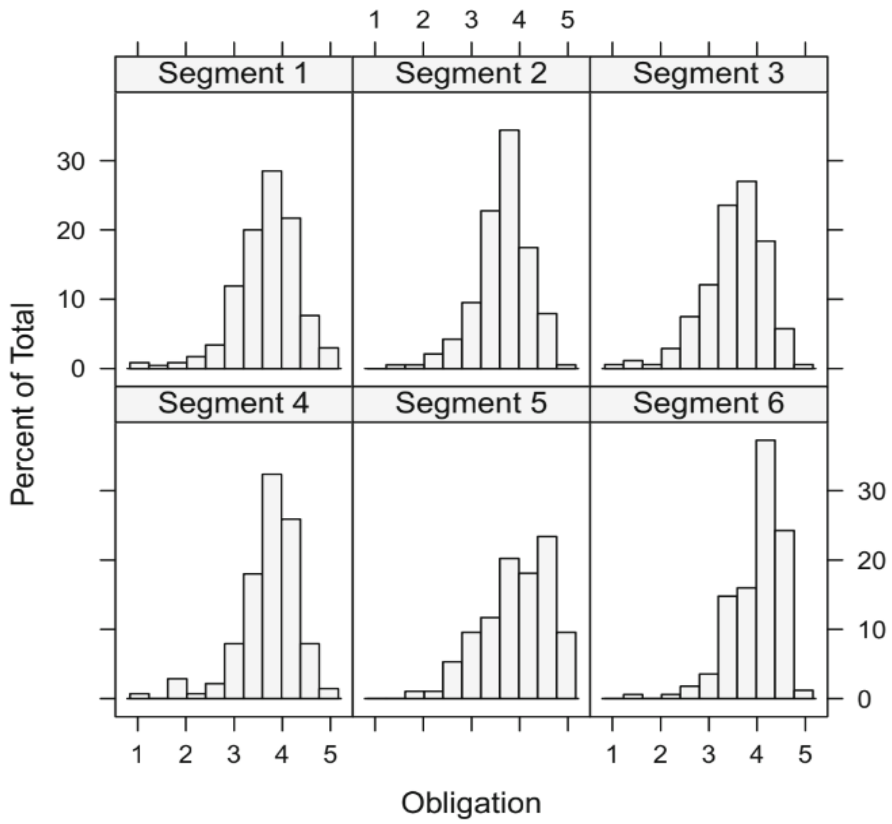

Fig. 7.6 Histograms of moral obligation to protect the environment by segment for the Australian travel motives data set.

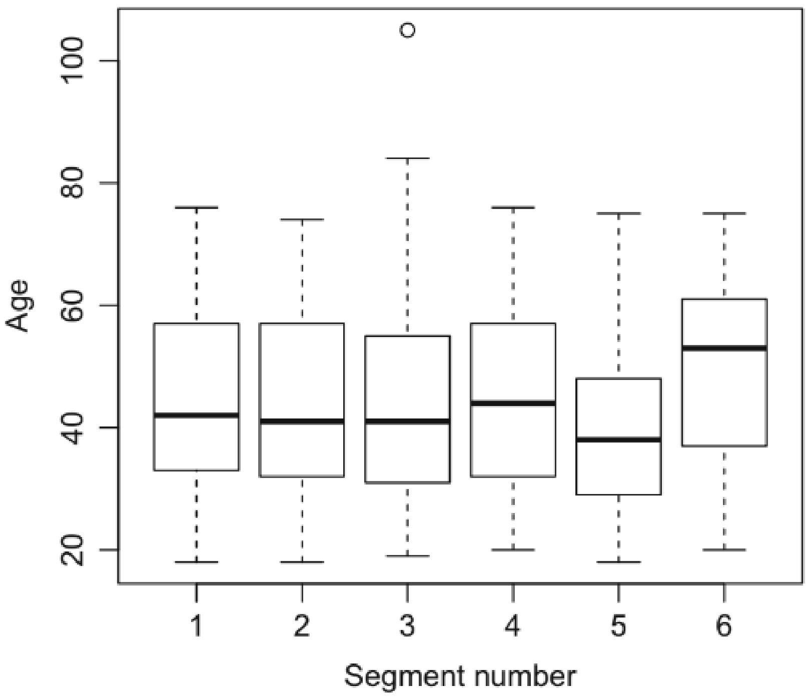

Fig. 7.7 Parallel box-and-whisker plot of age by segment for the Australian travel motives data set

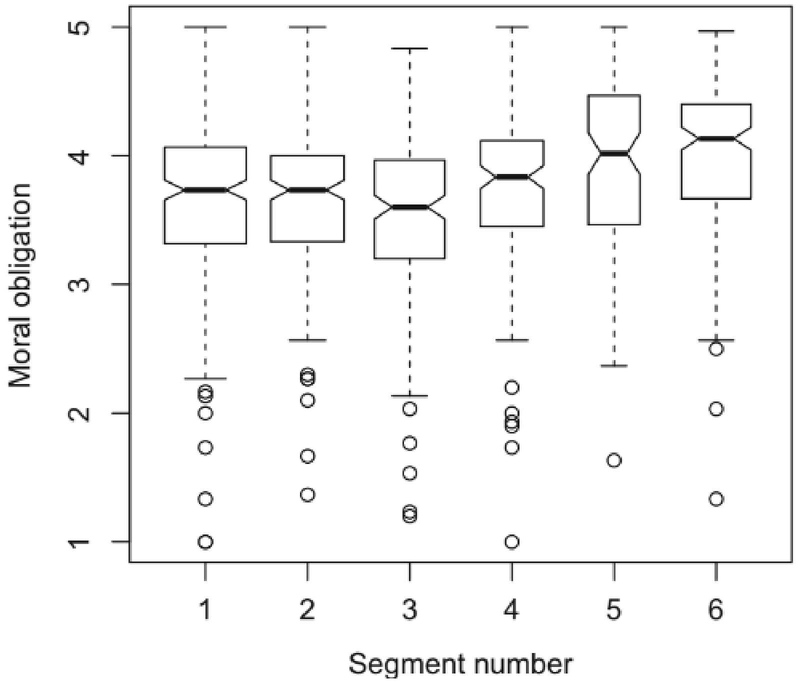

Fig. 7.8 Parallel box-and-whisker plot (with elements of statistical inference) of moral obligation to protect the environment by segment for the Australian travel motives data set

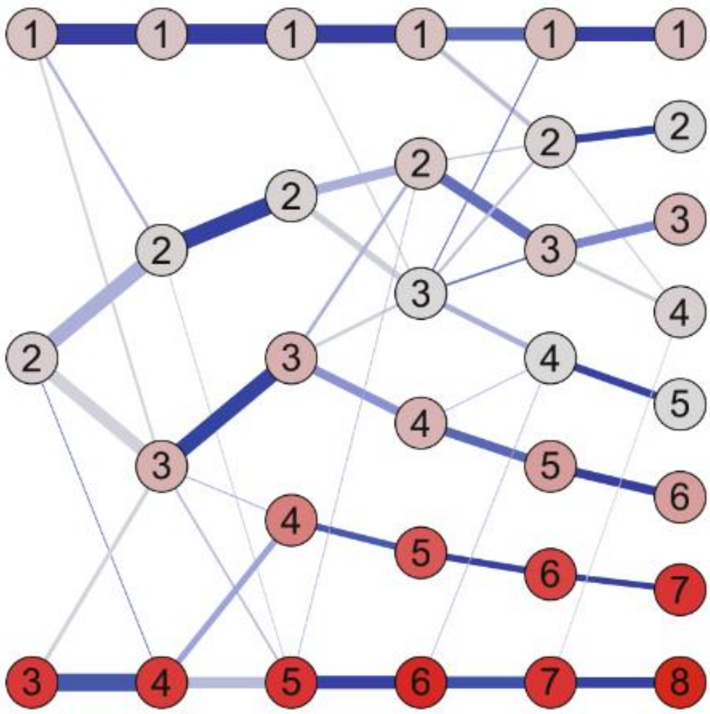

Fig. 9.9 Segment level stability across solutions (SLSA) plot for the Australian travel motives data set for three to eight segments with nodes coloured by mean moral obligation values

7.3 Testing for Segment Differences in Descriptor Variables

The process of formally testing differences in descriptor variables across market segments involves utilizing statistical tests. In particular, nominal or ordinal variables, such as segment membership, can be treated similarly to any other nominal variable for association tests. The $\chi 2$-test is commonly employed for this purpose, and the association between nominal segment membership and other variables is visualized using a mosaic plot. For example, to test for differences in gender distribution across Australian travel motives segments, the following R code and output are utilized:

chisq.test(C6.Gender)

The resulting output includes the test statistic (X-squared), degrees of freedom (df), and the p-value. A small p-value (< 0.05) suggests significant differences, while a non-significant p-value implies no rejection of the null hypothesis. To explore associations with metric variables, parallel boxplots and Analysis of Variance (ANOVA) are employed. ANOVA assesses mean differences among multiple groups, and the R code below demonstrates how to conduct ANOVA for mean moral obligation values across segments.

aov1 <- aov(Obligation ~ C6, data = vacmotdesc)

summary(aov1)

The F-test in the ANOVA output helps determine if there are significant mean differences among segments. In this case, a p-value less than 0.05 indicates rejection of the null hypothesis. Pairwise comparisons between segments are crucial for identifying which specific segments differ. R's `pairwise.t.test` function facilitates these comparisons, and the code snippet below provides an example:

with(vacmotdesc, pairwise.t.test(Obligation, C6))

This output includes adjusted p-values, which are essential when conducting multiple tests on the same dataset to control for inflated Type I error rates. Alternatively, Tukey's Honest Significant Differences (HSD) can be visualized to identify significant differences between segment pairs. The following R code generates the plot:

plot(TukeyHSD(aov1), las = 1)

mtext("Pairs of segments", side = 2, line = 3)

Figure 7.10 visually represents pairwise comparisons, where each row corresponds to a pair of segments, and significant differences are identified by confidence intervals that do not cross the vertical line at 0.

In summary, statistical tests, including the $\chi 2$-test, ANOVA, and pairwise comparisons, provide a rigorous framework for assessing differences in descriptor variables across market segments. Visualization tools like mosaic plots, boxplots, and Tukey's HSD plots complement these tests, offering a comprehensive understanding of segment characteristics and relationships with various variables.

Table 7.1 Differences in mean values for age and moral obligation between the six segments for the Australian travel motives data set together with ANOVA p-values

	Seg. 1	Seg. 2	Seg. 3	Seg. 4	Seg. 5	Seg. 6	Total	*p*-value
Age	44.61	42.66	42.31	44.42	39.37	49.62	44.17	1.699E-07
Moral obligation	3.67	3.65	3.55	3.72	3.93	4.01	3.73	3.300E-12

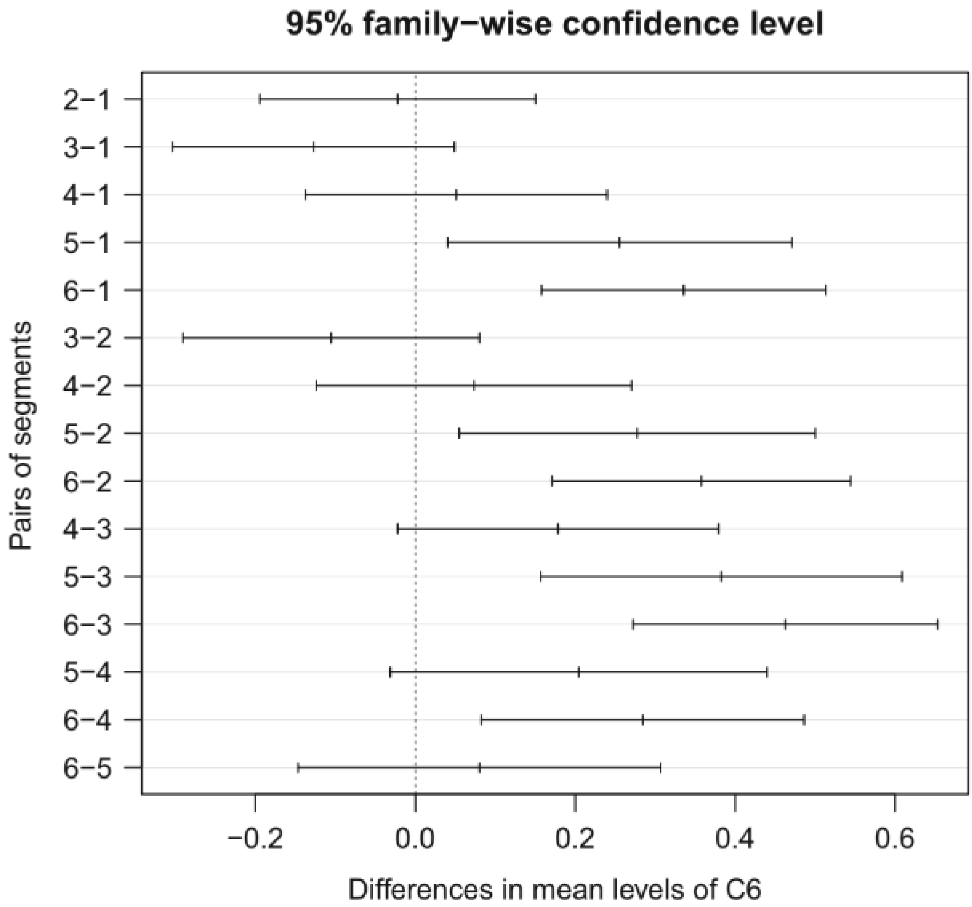

Fig. 7.10 Tukey's honest significant differences of moral obligation to behave environmentally friendly between the six segments for the Australian travel motives data set.

Github link: https://github.com/ShaikMdSiraj