1. Introduction

The improvement of service quality is often seen as a means to make public transport more attractive and competitive over individual transport modes. Transport researchers commonly analyse the mode choice with discrete choice analysis based on stated or revealed preference data. In stated choice experiments respondents are asked to choose between transport modes that are characterised by combinations of attributes with varying levels. It is therefore possible to analyse mode choice beyond the current alternatives. While focussing on attributes related to price and time, attributes related to service quality are often omitted or not analysed in detail. If too many attributes are included in common stated discrete choice experiments, the risk of high drop-out rates and biased results increases.

In the Hierarchical Information Integration (HII) approach [1] or its extension, the Integrated Hierarchical Information Integration (HII-I) approach [2], similar attributes are summarised by higher order constructs which
are included in choice or rating experiments. Therefore, a larger number of attributes can be analysed. Besides, in the HII-I approach it is possible to test for process equality [3], i.e. whether the data can be pooled into an overall model. One of the challenges in designing the experiments is the selection of attributes and their grouping into constructs. In most of the studies the grouping of attributes into constructs was based on literature studies and expert interviews. Constructs derived in that way might therefore differ from the respondents’ perception of constructs. Bos et al. [4, 5] proposed an empirical approach and applied it in the context of Park & Ride facilities to derive constructs which potentially led to more valid results. Respondents were asked to sort attributes into groups with respect to their perceived similarity so that attributes within one group were similar to each other but different from the attributes in the other groups. Dissimilarity data was analysed on aggregate level using a method of Multidimensional Scaling (MDS), i.e. dissimilarity data is represented by points in a multidimensional space such that the distances between the points fit the dissimilarity data as best as possible. Attributes that are often sorted in the same group are closer to each other in the MDS configuration than attributes that are rarely sorted together. While the method of sorting was new for deriving constructs for HII and HII-I, it has already been applied in different disciplines to categorise among others verbal concepts [6] social groups [7], food [8] or roadway [9]. Coxon [10] provides an extended list of studies using the sorting method. Beside its application in science, the method is used in usability engineering, where it is called Card Sorting. Results are used for example to structure websites or software in such a way that users can find information intuitively [11].

The MDS configuration fits the aggregate data best and the clusters found can be used as constructs. However, a good fit of the aggregate data does not necessarily mean that the clusters in the MDS configuration also correspond to the sorting at individual level. The problem especially occurs when data is sorted on a few, but very different criteria. When such paradigmatic sorting is expected, multidimensional scaling techniques are more appropriate than hierarchical clustering schemes which can generally also be used to analyse sorting data [6, 10].

The aim of the paper is to derive constructs related to service quality in regional public transport and to determine indicators of validity of the constructs. The constructs are later included in Integrated Hierarchical Information Integration experiments to analyse the choice between a regional train, a (hypothetical) regional bus, and a car (only available for car users). The same choice experiments are used for public and individual transport users, therefore, the constructs have to be valid both groups. To that end, sorting data is collected predominantly in interviews with train users but also with car users, serving as a control group. Data is analysed on aggregate level only for train users. The degree to which the clusters of the MDS solution correspond to the groups formed by the individual train users is an indicator for internal validity and the degree to which these clusters also correspond to the groups formed by the individual car users is an indicator for external validity.

To that end, the remainder of the paper is organised as follows: First, methodological aspects of Sorting and Multidimensional Scaling are presented in Chapter 2. The research design, the data collection and the sample are described in Chapter 3. In Chapter 4, the analysis is described and results are presented. Chapter 5 concludes and some aspects for further research are discussed.

2. Methodology

There are different ways to collect sorting data. The sorting technique relevant in this paper is disjoint free sorting, where a fixed set of \( n \) objects (service quality attributes) is sorted according to some criterion (perceived general similarity) into a respondent-chosen number of unlabelled groups. These groups are mutually exclusive and exhaustive, i.e. each object must be sorted into exactly one group [10].

The groups formed by each respondent are converted into a (dis)similarity matrix which is an \( n \)-by-\( n \) matrix. In a similarity matrix the cell \( c_{ij} \) contains the frequency that the pair of attributes \( i \) and \( j \) was sorted in the same group, whereas in a dissimilarity matrix the cell \( c_{ij} \) is contains the frequency that the pair of attributes \( i \) and \( j \) was sorted in different groups. The individual dissimilarity matrices are summed to obtain a dissimilarity matrix at
aggregate level. This aggregate dissimilarity matrix satisfies the axioms of metric measure [6] and is of ratio level: a 0 indicates that all respondents grouped a pair of attributes together while the highest possible value \( m \) indicates that none of the \( m \) respondents grouped the pair of attributes together.

Dissimilarity data can be analysed with Multidimensional Scaling (MDS), a method that “represents measurement of similarity (or dissimilarity) among pairs of objects as distances between points in a low-dimensional space” [12] such that the distances – in most applications Euclidean distances are used – represent the dissimilarities as best as possible. MDS models differ in the representation function that is used to approximate distances \( d_i(X) \) to transformed (dis)similarities \( f(p_{ij}) \). The sum of the squared error of representation over all pairs of objects yields a badness of fit measure which is called raw Stress \( \sigma_r \) (standardised residual sum of squares) for a given dimension:

\[
\sigma_r = \sigma_r(X) = \sum_{i,j} \left[ f(p_{ij}) - d_{ij}(X) \right]^2.
\]  

To avoid scale dependency, the raw Stress or the square root of the raw Stress are normalised in the stress measures Normalised raw Stress, Stress-1, and Stress-2 [13]. A different stress measure is the S-Stress that it is defined by the sum of the squared differences between the squared distances \( d_i^2(X) \) and the squared transformed (dis)similarities \( f(p_{ij})^2 \) and emphasises therefore larger dissimilarities more than smaller ones. S-Stress can also be normalized [12, 14]. The different scaling programs (such as the ALSCAL procedure and the more recent PROXSCAL procedure which are both included in SPSS Statistics) do not only differ in the Stress measures that are minimised but also in the iteration algorithms. While ALSCAL uses an alternating least-squares algorithm to minimise the S-Stress, PROXSCAL uses a subgradient method to minimise the normalised raw Stress [15, 16]. The normalised raw Stress is generally preferred to S-Stress because no a priori conversion is necessary since it is based on the distances and not on the squared distances.

The different stress measures indicate how well the aggregate dissimilarity data is arranged in a multidimensional space. However, they do not indicate how well the individual sorting data is represented.

The Rand index [17] (also called Simple matching coefficient) is commonly used to compare results of Hierarchical Cluster Analysis or to compare the similarity between two sortings [10]. It measures the correspondence between two classifications U and V and is defined by

\[
RI = (a + d)/(a + b + c + d),
\]

where

- \( a \) is the frequency that a pair of objects is in the same group in U and in V,
- \( b \) is the frequency that a pair of objects is in the same group in U but in different groups in V,
- \( c \) is the frequency that a pair of objects is in different groups in U but in the same group in V, and
- \( d \) is the frequency that a pair of objects is in different groups in U and V.

In other words, the number of correct pairwise classifications is divided by the total number of pairs. This index can also be used to compare the clusters of the MDS solution with the groups formed by an individual.

3. Research Design, Data Collection, and Description of the Sample

A list of 32 attributes related to service quality that potentially influence the choice of transport mode in regional transport was obtained in a literature study and in interviews with experts of three public transport
companies (Table 2). This list does not contain any safety attributes because analysing the influence of safety aspects on mode choice was beyond the purpose of the research.

Table 1: Stress measures for different numbers of dimensions

| Number of Dimensions | Normalised Raw Stress | Stress-I | Decrease of Normalised Raw Stress | Decrease of Stress-I |
|----------------------|-----------------------|----------|----------------------------------|----------------------|
| 1                    | 0.208                 | 0.456    | 0.792                            | 0.544                |
| 2                    | 0.067                 | 0.260    | 0.140                            | 0.196                |
| 3                    | 0.026                 | 0.162    | 0.041                            | 0.098                |
| 4                    | 0.011                 | 0.106    | 0.015                            | 0.056                |
| 5                    | 0.006                 | 0.076    | 0.005                            | 0.030                |
| 6                    | 0.003                 | 0.058    | 0.002                            | 0.018                |
| 7                    | 0.002                 | 0.046    | 0.001                            | 0.012                |
| 8                    | 0.001                 | 0.038    | 0.001                            | 0.008                |

A questionnaire for computer assisted personal interviews was programmed in MS Access. In the first part, some questions about the general travel behaviour were asked. The second part consisted in the sorting task with disjoint free sorting. Respondents were asked to group attributes with respect to their perceived similarity - independently of the importance - so that attributes within one group were similar to each other but different from the attributes in the other groups. To that end, the list of attributes appeared in a randomised order on the left side of the screen, preventing systematic ordering or fatigue effects. At the beginning, the right side of the screen was empty, no groups were created yet. Attributes could be placed one after the other with drag-and-drop on the right side of the screen, creating either a new group or adding the attribute to an existing group. Modifications were possible at any time during the sorting task. The number of groups was not restricted. Finally, respondents were asked to name each group to reflect their sorting. Since drag-and-drop could not be easily implemented in MS Access, Websort (www.websort.net) was used. The browser containing the study in Websort was automatically opened (internet was accessed via 3G sticks; sorting data could also be uploaded at a later time when the internet connection was temporarily unavailable) after the first part of the study. In the third part, respondents were asked to rate all 32 attributes on a scale ranging from 1 to 7 to indicate the importance of the attribute with respect to mode choice. The sorting task preceded the rating task because the order of the attributes in the rating task which was chosen by the researcher should not influence the sorting task. Finally, some demographic questions were asked in the fourth part of the interview.

Data was collected predominantly on-board regional trains in the Ruhr area and in Westphalia / Germany but also in vehicle registration offices in Westphalia. Respondents were approached by trained interviewers and asked if they were willing to participate. Altogether, 509 valid interviews were obtained, thereof 477 on-board trains and 32 in vehicle registration offices.

With 54.9% and 59.4%, respectively, a (small) majority of the respondents interviewed on-board and in the vehicle registration offices was male. Most of the respondents on-board (52.7%) were between 18 and 30 years of age and most of the respondents in the vehicle registration offices (65.5%) were between 31 and 50 years of age. 83.8% of the respondents on-board and all respondents in the vehicle registration offices had a driving licence. 73.5% of the respondents on-board and only 18.8% of the respondents in vehicle registration offices had a season ticket. The majority (68.1%) of the respondents on-board used the train a few times per week, whereas the majority of the respondents in the vehicle registration (50.0%) used the train rarely. In both groups, most of the respondents (39.6% and 87.5%) used the car a few times per week.

4. Analysis and Results
The data collected in the sorting task was stored among others in individual similarity matrices which are 32-by-32 matrices. The individual similarity matrices were converted to individual dissimilarity matrices.

In the first step, only the sorting data obtained in interviews on-board was analysed. Therefore, the 477 individual dissimilarity matrices containing the sorting data from the respondents interviewed on-board are summed to obtain an aggregate dissimilarity matrix. No weighting factor was applied. The smallest possible value in the cell $c_{ij}$ was 0, indicating that all respondents sorted the attributes $i$ and $j$ together, whereas the highest possible value was 477, indicating that all respondents sorted the attributes $i$ and $j$ in different groups. The aggregate dissimilarity data was analysed with Multidimensional Scaling using the PROXSCAL algorithm in SPSS for 1 to 8 dimensions. The RANDOM subcommand\(^1\) was used to select the starting configuration from multiple random starts using 100,000 draws. The convergence criterion which is the difference in consecutive stress values was set to 0.0001. The normalised raw Stress and the Stress-I values are displayed in Table 1. The Scree-plot of the normalised raw Stress plotted against the numbers of dimensions is displayed in Figure 1 but no “elbow” was found to determine the number of dimensions. The solution with three dimensions was finally chosen because the decrease of the normalised raw Stress of 0.041 is still substantial. A fourth dimension improves the normalised raw Stress slightly by 0.015. Besides, the interpretation of the results in more than three dimensions poses problems.

The three-dimensional solution corresponds to data points within a cube. In order to interpret the three-dimensional solution, orthogonal projections are displayed in Figure 2, showing (a) the x axis against the y axis, (b) the z axis against the y axis, and (c) the x axis against the z axis. Five clusters were found and indicated in the orthogonal projections. These clusters relate to (A) Quality of Connection, (B) Ticket Distribution, (C) Information, (D) Comfort, and (E) Security. Both Ticket Distribution and Security consisted of two sub-clusters that distinguish between on-board the train and at the station. Five attributes were not part of any cluster:

\(^1\) Results for this subcommand led to lower stress values than for the subcommands SIMPLEX or TORGERSON.
### Table 2: Clusters of Attributes and Results of Rating Data

| Cluster | Attribute | Rating Data collected on-board Regional Trains | Rating Data collected in Vehicle Registration Offices |
|---------|-----------|-----------------------------------------------|------------------------------------------------------|
|         |           | N    | Mean | SD   | Median | N    | Mean | SD   | Median |
| A       | Quality of Connection |       |       |       |        |       |       |       |        |
| 1       | Guarantee of connection | 434  | 5.81 | 1.39 | 6      | 30   | 6.27 | 1.28 | 7      |
| 2       | Frequency (trips offered per hour) | 433  | 5.38 | 1.18 | 5      | 30   | 5.50 | 0.97 | 5      |
| 3       | Total travel time (door-to-door) | 434  | 5.21 | 1.22 | 5      | 30   | 5.13 | 1.07 | 5      |
| 4       | No cancellation of trip | 433  | 6.45 | 0.86 | 7      | 30   | 6.30 | 1.15 | 7      |
| 5       | Punctuality | 434  | 6.24 | 0.94 | 6      | 30   | 6.27 | 0.78 | 6      |
| 6       | Frequency of having to change | 433  | 4.91 | 1.59 | 5      | 30   | 5.33 | 1.56 | 6      |
| B       | Ticket Distribution |       |       |       |        |       |       |       |        |
| B1      | Ticket machine at the platform (station) | 415  | 5.04 | 1.82 | 5      | 29   | 5.28 | 1.39 | 5      |
| B2      | Ticket machine on the train (train) | 414  | 4.85 | 1.80 | 5      | 29   | 5.14 | 1.33 | 5      |
| C       | Information |       |       |       |        |       |       |       |        |
| 12      | Announcements on the train concerning connection trains | 418  | 4.75 | 1.64 | 5      | 30   | 5.47 | 1.53 | 6      |
| 13      | Announcements at the platform in case of troubles or delays | 427  | 6.37 | 0.98 | 7      | 30   | 6.47 | 0.68 | 7      |
| 14      | Announcements on the train in case of troubles or delays | 427  | 6.31 | 1.01 | 7      | 30   | 6.47 | 0.73 | 7      |
| 15      | Timetable information at the platform | 429  | 5.70 | 1.36 | 6      | 30   | 5.97 | 0.89 | 6      |
| 16      | Information display at the platform in case of troubles or delays | 425  | 6.26 | 1.02 | 7      | 30   | 6.43 | 0.63 | 7      |
| 17      | Information display on the train (outside) | 419  | 4.64 | 1.63 | 5      | 30   | 5.57 | 1.14 | 6      |
| 18      | Information display on the train concerning connection trains | 409  | 4.82 | 1.56 | 5      | 30   | 5.17 | 1.51 | 5      |
| D       | Comfort |       |       |       |        |       |       |       |        |
| 20      | Free space on the train (for example for luggage, bikes, prams,…) | 432  | 4.12 | 1.80 | 4      | 30   | 4.37 | 1.73 | 5      |
| 21      | Comfort of seats | 433  | 4.43 | 1.46 | 4      | 30   | 4.13 | 1.50 | 5      |
| 22      | Cleanliness of toilet on the train | 430  | 5.40 | 1.69 | 6      | 30   | 5.97 | 1.65 | 7      |
| 23      | Cleanliness of train outside | 429  | 3.39 | 1.66 | 3      | 30   | 3.17 | 1.49 | 3      |
| 24      | Cleanliness of train inside | 430  | 5.63 | 1.17 | 6      | 30   | 6.03 | 0.96 | 6      |
| 25      | Seat availability on the train | 433  | 4.94 | 1.51 | 5      | 30   | 4.90 | 1.52 | 5      |
| E       | Fare |       |       |       |        |       |       |       |        |
| 26      | Fare | 432  | 5.65 | 1.40 | 6      | 30   | 5.80 | 1.24 | 6      |
| E1      | Security |       |       |       |        |       |       |       |        |
| (station) | Security personnel at the platform | 417  | 5.13 | 1.68 | 6      | 30   | 5.67 | 1.45 | 6      |
| E2      | Security personnel on the train | 416  | 4.96 | 1.70 | 5      | 30   | 5.03 | 2.09 | 6      |
| (train) | Video surveillance on the train | 417  | 4.77 | 1.83 | 5      | 30   | 5.17 | 1.95 | 6      |
| Waiting Shelter at the Platform |       |       |       |       |        |       |       |       |        |
| 31      | Waiting shelter at the platform | 419  | 4.17 | 1.70 | 4      | 30   | 4.97 | 1.45 | 5      |
| Comprehensibility of Tariff System |       |       |       |       |        |       |       |       |        |
| 32      | Comprehensibility of tariff system | 411  | 6.00 | 1.23 | 6      | 29   | 6.62 | 0.62 | 7      |
Friendliness of Personnel, Timetable Information in the Internet, Fare, Waiting Shelter at the Platform, and Comprehensibility of the Tariff System. An Overview of the clusters and their attributes is given in Table 2, along with means, standard deviations, and medians of the rating data, displayed separately for data collected on-board and in the vehicle registration offices. High values of standard deviations indicate that respondents rate the attributes differently. Especially attributes related to the clusters Ticket Distribution and Security have high standard deviations.

The five clusters and five separate attributes constitute the MDS solution of aggregate data. In the next step, Rand indices were calculated to analyse how well this aggregate solution fits the groups formed by each individual. The distribution of Rand indices for the data collected on-board regional trains can be seen as an indicator for internal validity whereas the distribution of Rand indices for the data collected in vehicle registration offices can be seen as an indicator for external validity since this data was not included in the MDS analysis. The distributions of Rand indices are displayed in Figure 3 (a) and (b). The means of the Rand indices for the sorting data collected on-board and in vehicle registration offices were 0.78 and 0.75, the standard
5. Conclusion and Discussion

The aim of the paper was to derive constructs related to service quality in regional public transport and to determine indicators of validity of the constructs. To that end, a list of 32 attributes was obtained in a literature study and in interviews with experts of three public transport companies. In interviews on-board regional trains and in vehicle registration offices, respondents were asked to sort these attributes with respect to their perceived similarity. The sorting data collected on-board was analysed with Multidimensional Scaling. Five clusters related to Quality of Connection, Ticket Distribution, Information, Comfort, and Security were found. Besides, some attributes were not part of any cluster. Rand indices were calculated as indicators of internal and external validity. Results show that the individual data is rather well represented by the aggregate solution.

The approach proposed by Bos et al. [4, 5] was closely followed with some minor modifications: free sorting was used, whereas Bos et al. restricted the number of possible groups to six. In their pre-test, respondents hardly used more than six groups. However, this limitation cannot be generalised since the number of groups depends among others on the attributes to be sorted. In this study, a quarter of respondents used more than 6 groups (average number groups: 5.6 groups, standard deviation: 2.4, median: 5). Free sorting overcomes the problem that respondents have to modify their sorting due to the maximum number of groups. Besides, an MDS procedure based on the minimisation of the normalised raw Stress rather than the S-Stress was used so that small and large dissimilarities are equally emphasised. Finally, Bos et al. calculated MDS solutions for different sub-groups of respondents but did not report how the aggregate solution fits the individual data.

The influence on the selection of constructs on the outcome of the HII or HII-I experiments is rather unexplored. In a residential preference study with 70 architecture students, Oppewal and Klabbers [18] analysed different hierarchical structures of two HII experiments that were designed as rating experiments. In both experiments, the same set of attributes was used but attributes were grouped into different constructs: in the first experiment, the constructs constituted different characteristics (such as size or sunlight) of rooms while the attributes constitute the type of the room (such as living room or kitchen) with the given characteristic. In the second experiment, the constructs constituted the different types of rooms while the attributes constitute the characteristics for the given room. No differences in the preference structure were found. Besides, respondents were asked to rate the easiness of the experiments. The easier HII task had a higher hit rate but the differences were not significant. They concluded that differences in the hierarchical structure can result in task load differences that do not necessarily result in measurement or model performance differences. More research is necessary to explore whether this finding can be generalised.

Three of the five clusters derived in this study, namely Quality of Connection, Comfort, and Information, were included as constructs in HII-I experiments to analyse the choice between a regional train, a (hypothetical) regional bus and a car (only available for car users). Attributes with low means related to these clusters were omitted while some similar attributes were summarised by a new attribute. The attributes of the clusters Ticket Distribution and Security had rather low average rating values and high standard deviations. The ratings for the attributes relating to Ticket Distribution might be biased by fact that many respondents had a season ticket. Some of the respondents were very averse to video surveillance which is in line with research on cross-country differences in the acceptance of video surveillance [19, 20]. It was found there that respondents in Germany were rather sceptical towards video surveillance. Therefore, these two clusters were not included in the HII-I experiments. The design of the HII-I experiments is described in Richter and Keuchel [21]. Process equality was

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2 Rand indices were also calculated for the aggregate solution with the sub-clusters of Distribution and Security that distinguish between on-board and at the station. However, the solution without sub-clusters led to higher average Rand indices.
tested and it was found at least for a part of the data. That means that the data could be pooled into an overall model containing all attributes [21, 22]. The constructs that were derived in this paper have probably improved the respondents’ understanding of the relationship between the attributes and the constructs in the HII-I experiments. The empirical deriving of constructs described in this paper may be one reason for the finding of process equality.

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