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Transportation Research Procedia 76 (2024) 258–268

Transportation Research Procedia

www.elsevier.com/locate/procedia

12th International Conference on Transport Survey Methods

Checking Data Quality of Longitudinal Household Travel Survey Data

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Abstract

Ensuring data quality of household travel survey data is often tedious and, thus, time-consuming. To speed up the process of data-checking and to gain an in-depth understanding of the data, data visualization is a practical, fundamental tool. Since 1994, data visualization has been used in the German Mobility Panel (MOP) data-checking process. This paper presents two graphical visualization tools developed for the MOP. Both tools speed up the data checks and ensure high consistency in identifying erroneous data. This paper describes and discusses how the tools provide a continuous data quality assessment.

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Peer-review under responsibility of the International Steering Committee for Transport Survey Conferences (ISCTSC)

Keywords: data visualization; plausibility checks; data quality; longitudinal data; German Mobility Panel (MOP); GraDiV

1. Introduction

For various reasons, missing values and incorrect or implausible information occur in most raw datasets of household travel surveys. Thus, ensuring data quality forms an essential step of data processing. This often requires efforts to filter implausible data. For example, there is a common problem in travel surveys that data may seem implausible though sensible (e.g., children sleep in schools on rare occasions), which is challenging to identify. The completeness, quality, and consistency are essential, especially for travel survey data, to provide reliable datasets suited to base further analyses (Sammer et al. 2018). Therefore, it is crucial to edit the data cautiously – as much as necessary but as little as possible.

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10.1016/j.trpro.2023.12.053

Data-checking of household travel surveys is often tedious and time-consuming, thus costly (Kandel et al. 2011). Manual data checks with data visualization help to improve data quality and to understand the data in all its facets in general. However, to check the data, checking staff is needed. This involves teaching them the fine balance between what is right or wrong and (un-)necessary in advance. How to support and supervise the nuanced human judgment of data-checking is a very fundamental question of data post-processing and interlinked with the use of data visualization.

The primary motivation for this paper is to illustrate challenges regarding the visualization of travel survey data to assess data quality. Furthermore, our motivation for data visualization in the checking process is that solely algorithm-based checks alone are insufficient for household travel surveys. The nuanced human judgment is indispensable throughout travel data processing and preparation, especially in distinguishing between implausible and unusual but plausible reports. Data visualization is a powerful tool to enhance the understanding of data and thus assess data quality. In this context, this paper presents the well-established and reliable design of two different tools for "*Graphical diagnosis of individual travel behavior"* (GraDiV) used for our research.

Since 1994, the Institute for Transport Studies of the Karlsruhe Institute of Technology has been commissioned with the scientific supervision and data preparation of the German Mobility Panel (MOP), a longitudinal national household travel survey. The MOP repeatedly collects data on individual travel behavior in Germany for one week. Furthermore, the MOP gathers data about mileage and fuel consumption of cars used by the MOP households for eight weeks (Ecke et al. 2020). Since both parts of the survey result in complex data, multi-faceted checks for their processing have been developed. These checks include both automated, rule-based checks and data visualization tools for assessing data quality by identifying potential implausibilities and data flaws.

The main asset of the MOP survey is the ability to provide longitudinal data. The survey has seen only minor adaptions in the data quality assessment and checks since the beginning in 1994 (Chlond et al. 2015; Eisenmann et al. 2018b, 2018a), which ensures the comparability of survey results over decades. In 1996, the initial version of the first GraDiV tool was implemented for the data-checking process in the everyday travel survey of the MOP. In 2015, the second GraDiV tool was implemented for the data on mileage and fuel consumption. The tools are designed explicitly for the MOP data and enable an effective inspection of travel data. While having been continuously improved, the tools still ensure the same basic principles of data quality checks.

This paper gives insights on how data-checking is carried out in the MOP. For this aim, we provide deep insights into the design and application of GraDiV. The paper is structured as follows: First, we describe the literature review results on general quality checks, particularly for travel data. Then, we introduce the MOP surveys on travel behavior and mileage/fuel consumption. Next, we give insights into both survey parts' data processing and present a structured inspection of different types of travel data using GraDiV. We highlight how data visualization helps to understand the complexities and variabilities in travel behavior and brings the data into a (sensible) form for further use. Lastly, we discuss additional steps and improvement methods for future work.

2. Literature Review

Missing data, wrong data and duplicates in data sets (e.g. trips) produce incorrect and misleading results. Therefore, data quality management is essential and highly relevant for all those who work with the data. Plausibility checks, in general, allow the identification of incorrect information. In travel data, for example, this can be a disproportionately high speed in combination with the means of transport reported. The correction of such implausible information is usually rule-based. Additionally, if important information is missing, imputation procedures can be applied. There are many different methods ranging from regression-based approaches to machine learning (Doove et al. 2014; Stekhoven und Bühlmann 2012; Rodríguez de Gil und Kromrey 2013). However, the disadvantages and potentially negative influences of imputation should be considered when applying imputation methods.

Griffith et al. (2000) emphasize the relevance of detailed and accurate data on travel behavior through editing, validating and processing. However, hardly any information on the data processing and plausibility-checking processes performed can be found in the literature and the reports on travel surveys. No detailed information on the exact procedures is given.

Data visualization is a proven tool for developing an understanding of travel. In the past, data visualization has been applied in many travel surveys (Wallner et al. 2018; Buliung et al. 2008; Schönfelder 2006). However, these studies do not focus on data visualization for data-checking.

In the following, our literature review focuses on how institutions that manage travel survey data process their data quality assessment, as this is essential for high data quality. Information on data preparation is available for the National Household Travel Survey (NHTS) in the U.S. (NHTS 2018). In the online survey, checks for implausible answers are performed in real-time during questionnaire completion. The participant receives a warning if implausible or missing information is detected. Further automated checks identify potential errors in the data analysis process, including missing data and unlikely travel behavior. In the NHTS, slight modifications are performed to edit reported trips. For this, five aspects are relevant: Location, joint travel, time and speed, misreported loop trips and first/ last place misreported. The data editing process is described in (NHTS 2018). It is important to note that if variables are imputed or recalculated, the data reported by the participants are not updated or replaced in the NHTS. The information is provided in form of new variables. The National Travel Survey in Ireland (NTS 2015) provides other examples of data editing and imputation processes. Only missing variables for trips are imputed with a nearest neighbor imputation method. Limited data editing is performed if answers do not correspond to a predefined list of answers.

Data assessment and imputation procedures are also applied in German travel surveys, e.g. in the NHTS "*Mobility in Germany*" (MiD). This applies to the variables at the trip level, e.g. "main means of transport", "distance traveled" and "travel duration". For the sociodemographic variables, missing values for net income are also imputed. Furthermore, filter functions are used to track why a value is missing and how this inconsistency is handled (Nobis et al. 2019). Additionally, there are checks on whether certain variables lie within defined ranges of values. Here, adjustments of inconsistencies by plausibility checking rules, considering several variables, are employed (upon detection). In case of doubt, the inconsistency remains(Eggs et al. 2018).

Another travel survey “*Mobility in cities – SrV 2018*” first uses algorithmic checks for the incoming raw data to check for implausibilities. Subsequently, individual checks are performed/executed with the help of a database application based on Microsoft Access (Hubrich et al. 2019). The separate reviews allow adequate data inspection but are time-consuming (Hubrich 2019). These examples demonstrate that, in general, travel surveys require plausibility checks and data processing to ensure sufficient data quality for further usage.

More examples of data visualization for data-checking can be found in other research fields. For instance, Arbesser et al. (2017) implemented a visualization tool to check data relating the energy sector. Gschwandter et al. (2018) used data visualization to differentiate between data quality problems and unusual but valid time series data from the geological industry. Tableau is mentioned as a standard data visualization tool for reporting data types (Tableau 2020).

Based on the literature overview, we come to the following conclusion: Although data-checking processes are essential for improving survey data quality, only a few institutions (publicly) provide information on their processes. If the data-checking and editing processes are explained, it mostly occurs on a very abstract level. To the authors’ knowledge, only a few institutions working with travel surveys use data visualization for their checking processes. However, in other fields of research, the application is more widely spread. We further conclude that data visualization of travel behavior is deployed, though not for data-checking processes. We identify a lack of literature and information on the scientific assessment of data-checking applications in travel behavior research. With this paper, we contribute to the research by presenting two visualization tools used in the data-checking processes of the German Mobility Panel.

3. Survey Data - German Mobility Panel

The MOP is a national household travel survey collecting data on the travel behavior of the German population since 1994. It is designed as a rotating panel. Participants are asked to take part for three consecutive years. Participation is voluntary. The MOP allows insights into cause-effect relationships utilizing a temporal longitudinal perspective for everyday travel behavior as well as car mileage and fuel consumption of private households. The study has undergone only a few methodological adjustments in the past to compare the results on travel behavior between years as unbiased as possible from methodological influences. Since the beginning of the MOP, the data has been checked using data visualization tools as part of the data preparation process. Generally, the MOP consists of two parts as described in the following.

3.1. Survey About Everyday Travel Behavior

The first part of the survey collects data on everyday travel behavior. Approximately 3,000 individuals (1,800 households) participate in the survey each year. It takes place in the fall and covers a survey period of one week. All household members above ten years old are asked to complete a trip diary. The trip diary provides information about all trips during seven consecutive days (one week), i.e., distances, means of transport used, trip purposes, and departure and arrival times of trips. Furthermore, the corresponding household fills in a household questionnaire, which provides information about the sociodemographic characteristics of the household and all household members.

3.2. Survey About Car Mileage and Fuel Consumption

In addition to the survey on everyday travel behavior, households owning at least one car are asked about mileage and refueling events of their cars. This part of the survey takes place in the spring of the subsequent year and covers a survey period of eight weeks (April to June). In this part of the survey, information about approximately 1,600 cars of 1,200 different households is collected. The participants are asked to fill in a fuel logbook reporting all refueling events (date, odometer reading, amount of gasoline dispensed, refueling cost). Furthermore, car characteristics (e.g. year of construction, engine capacity) and car usage patterns (e.g. number of users, special features during the survey period) are reported.

4. GraDiV – Visualization Tools for Data-checking in the MOP

Based on the long-term monitoring of the MOP we were able to develop a multi-faceted plausibility procedure for the MOP data, which includes preprogrammed rule-based checks as well as data visualization as part of the data-checking process. In 2015 we completed the (re-)implementation of the GraDiV tools. In the following, we describe the process of data preparation and checking for both survey parts. We highlight how data visualizations help identify inconsistencies in the data and achieve the data quality suitable for further analysis.

4.1. Data Checks for Everyday Travel Behavior Data

Pre-checks and Data Preparation

In the first step, we use algorithms to check the sociodemographic information on the household and person levels. The longitudinal design of the MOP allows the usage of the data of previous years for the identification of implausible information on households and persons (e.g. level of education depending on age). We also use data from the previous year to replace missing values of people reporting for the second/third time. The pre-checks allow for a high consistency of the sociodemographic data of individuals, which is essential for trip diary checking.

Individual Data Checks Based on GraDiV

This step consists of inspecting the trip diaries. GraDiV displays the travel data of individual trip diaries for the whole week graphically (Figure 1). The data of each trip, such as the day of the week, start and end time, trip purpose, distance, speed and the modes used, is shown in element (1). This data is additionally visualized in detail (2). The visualization starts with the first day of the report, which is not necessarily Monday due to varying starting days. The abscissa represents the hours/time of the day. A trip is graphically elevated in the row and the used transport mode is indicated by color. Furthermore, trip purposes (activities) are also visualized in color. The duration of the activity depends on the end time of the last trip and the start time of the next trip. Rule-based checks indicate implausibilities, for example, if the calculated speed exceeds typical speeds of the reported mode. Such implausibilities are highlighted in red in the table. Possible reasons for a high speed are, for example, a wrong transport mode assigned to this trip, a false start- or end-time, or an incorrect report of the distance traveled. Visualization (2) (easily) allows the assessment of a person's "typical" behavior over the week. For instance, some people solely use the car for all their trips or take the same bus connection every day to commute to work. Identifying such patterns in the visualized travel behavior is one of the main benefits of this tool.

Further information is given by the sociodemographic characteristics of the person, which are depicted in (3). Information about the entire household and other specific information about the person is provided, such as having a driving license or whether the person was ill or on holiday for one or more days during the completion of the trip diary. This information helps the checking staff to assess, for example, whether a person was not mobile or whether reporting was missed for one or more days. Furthermore, participants from the same household can be visualized simultaneously, allowing joint trips and activity identification (4).

The elements (1) and (2) represent the core elements of the visualization tool. Irregularities (e.g. implausible speeds) and minor faults (typing errors of departure or arrival times) are displayed and easily identified and corrected. The staff is instructed to check for specific cases, e.g. distinguishing loop trips such as walking the dog or identification and completion of missing values based on data of other reported days. If a household member reported implausibilities, the data can easily be adapted. Besides adjusting the attributes of the reported trips, new trips can also be inserted (5). A typical scenario is if someone has not reported a trip back home from shopping (Figure 1, (2), Saturday). In the visualization, it looks like the person is staying overnight at a shopping location. In this case, it is useful to add a way home from shopping.

If a change does not raise the plausibility of the trip diary, the last change or the entire data set of the person can be reset to the original form. Finally, the checking staff judges whether the person's trip diary appears plausible, whether there are still open questions to be discussed or whether the trip diary is in such an implausible state that it may have to be removed from the data set (6). The latter case is critically reviewed in the subsequent post-check.

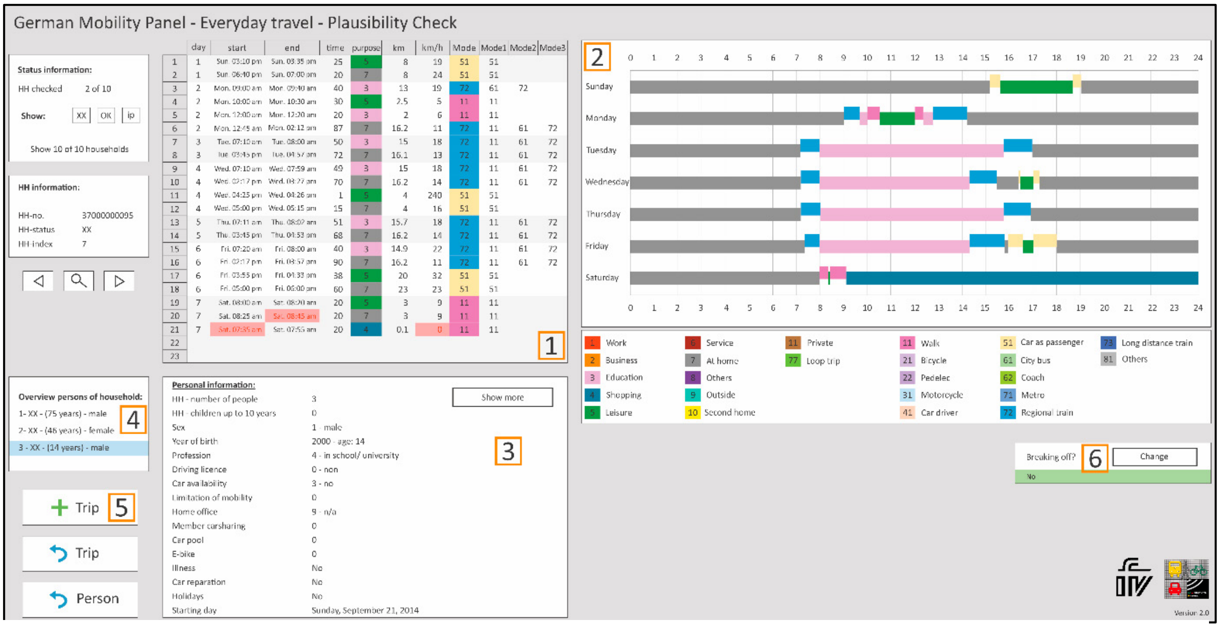

Figure 1: Data visualization in GraDiV - the data of a one week trip diary is displayed

Post-checks

The characteristics of the MOP allow for identifying participants who provide implausible reports during the week, e.g., trip reports only during the first days. Trip diaries with blatant deficiencies identified in the individual data check are critically reviewed again. For repeaters who participated in previous years, trip diaries of earlier years are also included for comparison. The post-checks also allow the exclusion of trip diaries with such deficiencies.

Due to the high effort required to collect each diary, this is only done in some cases as an exception to improve the overall quality. The post-checks are performed by different persons of the checking staff than those who performed the individual data checks (dual control principle).

Detected Errors

The described checks and the systematic application of defined rulesets for the data checks result in a high consistency and quality for further analysis.

Table 1 displays the percentage of edited trips between 2011 and 2018. The percentages of edited trips of all trips are differentiated by the type of editing. It becomes clear that the new implementation of the visualization tool in 2015 did not cause remarkable changes in the identified types of errors. However, a rather considerable change is noticeable when looking at the identification of loop trips between 2016 and 2017. That year, the institute in charge of the data collection included the identification of loop trips in their processes. Altogether, the table underlines the low percentage of data editing necessary in the data plausibility checks.

Table 1: Percentage of edited trips differentiated by the type of editing and year

Generation	**GraDiV tool 4th generation**				**GraDiV tool 5th generation**			
Year	2011	2012	2013	2014	2015	2016	2017*	2018*
Type of data editing								
Insert, delete, merge trips	0.2 %	0.2%	0.3%	1.1%	0.5%	0.3%	1.2%	1.2%
Insert, delete, edit of mode	1.1 %	2.8%	0.2%	0.8%	0.1%	0.2%	0.2%	0.2%
Edit of start or end time	1.9 %	1.5%	0.7%	2.5%	1.9%	1.9%	1.8%	2.0%
Edit of trip distance	0.3 %	0.2%	0.3%	1.1%	0.3%	0.2%	0.2%	0.4%
Edit of trip purpose	0.5 %	0.4%	0.3%	0.9%	1.0%	0.7%	0.3%	0.5%
Identification of loop trips	3.7 %	3.3%	3.4%	3.8%	3.9%	3.3%	0.8%	0.7%

In 2017 and 2018 loop trips were also identified by the fieldwork institute

The implementation of the 5th generation GraDiV for assessing data quality in the trip diaries in 2015 brought forward another benefit. A faster and more efficient working pace compared to the 4th generation is achievable. We cannot precisely compare the time saved before and after implementing the new generation of the tool due to a lacking degree of detail in time recording. However, we estimate that the time effort is reduced by about 30 %. We conclude that improving data visualization reduces the overall workload for the checking staff.

4.2. Plausibility Checks for Data on Mileage and Fuel Consumption

Besides reimplementing the GraDiV tool to inspect trip diaries, we also decided to use data visualization to identify implausibilities in the mileage and fuel consumption data. In 2015, we completed the implementation of another GraDiV tool, where the checking process contains multiple facets, including iterative loops to assess data quality. It consists of three steps, which we describe in the following.

Pre-checks and Data Preparation

The pre-checks aim to identify incorrect and incomplete information about the cars (e.g., missing or particularly high or low cubic capacity which is essential for weighting). For these checks, it is essential to have plausible and complete car information. The pre-checks consist of two parts:

- Checks for missing values on car characteristics: People often do not know specific information about their cars, which causes missing values. We use algorithmic checks to decide whether missing values can be added based on data from previous years. The checks are necessary because the identification of identical cars between years is based on car characteristics. Slight deviations, e.g. in engine capacity, often forestall the re-identification.

- Data checks for implausibilities in car characteristics: The cross-checks are also based on previous years and manufacturer information. This step contains the checking of the purchase year or the construction year, mileage in the reporting period, and implausibilities for fuel capacities, displacement, and horsepower.

We use the car information for the individual data-checking process of refueling events which we describe in the following.

Individual Data Checks of Refueling Events

The pre-checks ensure the completeness and plausibleness of the information on car characteristics so that we can use it for the checking process of the refueling events, where the GraDiV tool is again utilized. Because the data differs from everyday travel data, a new tool was developed that is tailored to the specific demand. Figure 2 illustrates the GraDiV tool we use for the checks of the logbook data on mileage and fuel consumption.

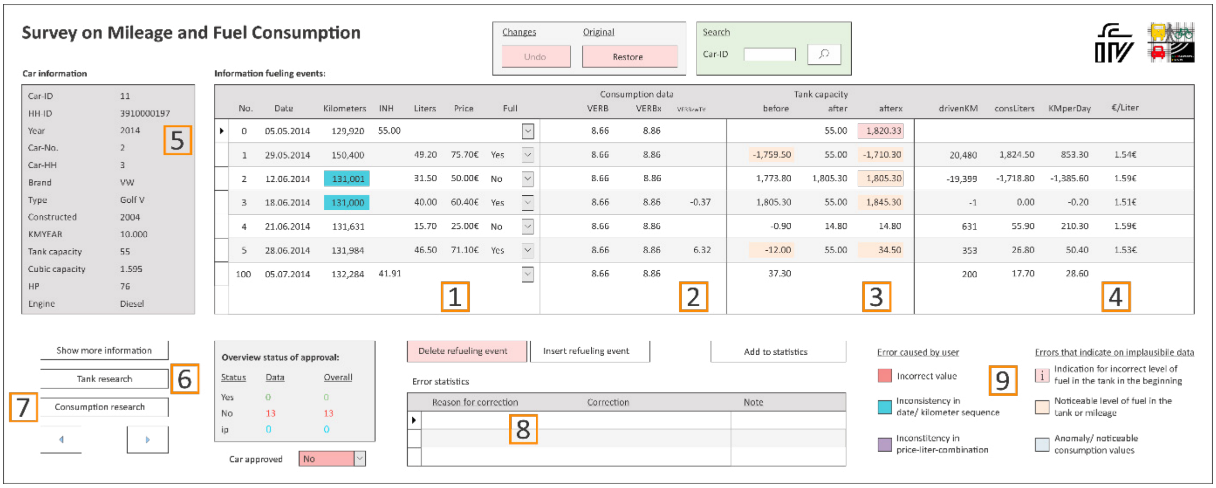

Figure 2: Visualization tool for logbook data on mileage and fuel consumption

The key idea is to graphically highlight implausibilities. The interface consists of several parts: The core elements are shown in a table, including the elements (1) - (4). The left part depicts the given information of the reported refueling events (1). The first row of the table displays the start date and fuel level in the beginning of the survey period. The last row presents the level at the end of the survey period. The rows in between show the data for each refueling event (one row per refueling event). The fuel level can only be edited in the first/last row (beginning/end of the reporting period).

The data can be adjusted in (1). The additional information displayed in (2) - (4) is calculated by a data model. For example, the fuel levels before and after the refueling events (3) are determined automatically based on the information for all reported refueling events. Furthermore, the tool calculates the fuel consumption rates (2). It also counts the kilometers driven between refueling events as well as the fuel consumption, kilometers per day and fuel price per liter, respectively (4). The information is essential for data evaluation as the structured overview helps to speed up the identification of implausibilities.

The information on car characteristics is provided in (5). Furthermore, detailed information on sociodemographic household characteristics can be found. The information helps to understand the refueling behavior of car drivers.

Moreover, two databases providing additional information on fuel capacities and fuel consumption are integrated into the tool and described in the following.

Databases on Fuel Capacities (6) and Fuel Consumption (7)

People not being aware of the exact fuel capacity of their car is a common occurrence. However, the fuel capacity is an essential variable for the tool. We check the fuel capacity in the pre-checks, but we only correct extraordinarily high or low fuel capacities. The database on fuel capacities contains information for all car types that have ever been recorded in the survey. The database allows for the correction of fuel capacities in case of incorrect data. If the data seems to be incorrect, it is highlighted in (2) - (4). After the correction, the model recalculates the indicators displayed in (2) - (4). The data base only operates on an aggregate level because individual comparison does not work for many brand-model combinations due to small sample sizes. The tool indicates possible implausibilities if the key values are outside of a specific range of the database values.

Furthermore, information on fuel consumption for every car type ever recorded in the MOP is provided in a database. We use this database to compare the refueling data with plausible data from previous years. The database helps to speed up the decision process.

Checking Process

This section describes how we operate the GraDiV tool to identify implausible data. The process consists of a predefined workflow. In the end, all data adaptions are documented by the checking staff. The workflow ensures high data consistency and quality and is displayed in Figure 3. The process starts by checking for implausibilities (Figure 2, (1) - (4)). If there are no errors, the data is approved. For the data checks, we distinguish two types of errors that differ in (levels of) severity:

- Errors caused by erroneous reporting (e.g. missing or incorrect values): Such errors are caused by participants that actually knew (or were able to know) the real data but made a mistake while writing it down. E.g. a date of a refueling event, which is not in the survey period, is reported. Identifying such a mistake is visualized in the tool. It must be corrected so that the date of the report ranges in the survey period and is consistent with other refueling events. Another example is too high/low fuel prices. To assess this aspect, we research the average fuel price of the survey period (and minimum/maximum) to adjust the upper and lower limits for this check. If the price is outside the limits, it is necessary to check whether the price or the liters filled cause an error.
- Errors that indicate implausible data are caused by participants that did not actually know the information and guessed erroneously. This is the case, for example, when the initial tank capacity is reported incorrectly. This can lead to inaccuracies e.g. extreme fuel consumptions between refueling events or a fuel amount of a refuel event above tank capacity.

In the tool, potential implausibilities are highlighted in color. If a correction is necessary, a predefined set of correction options is provided. All manual corrections are documented in table (8) (Figure 2), where the error of the highest priority is documented as the trigger fo change (9) (Figure 2).

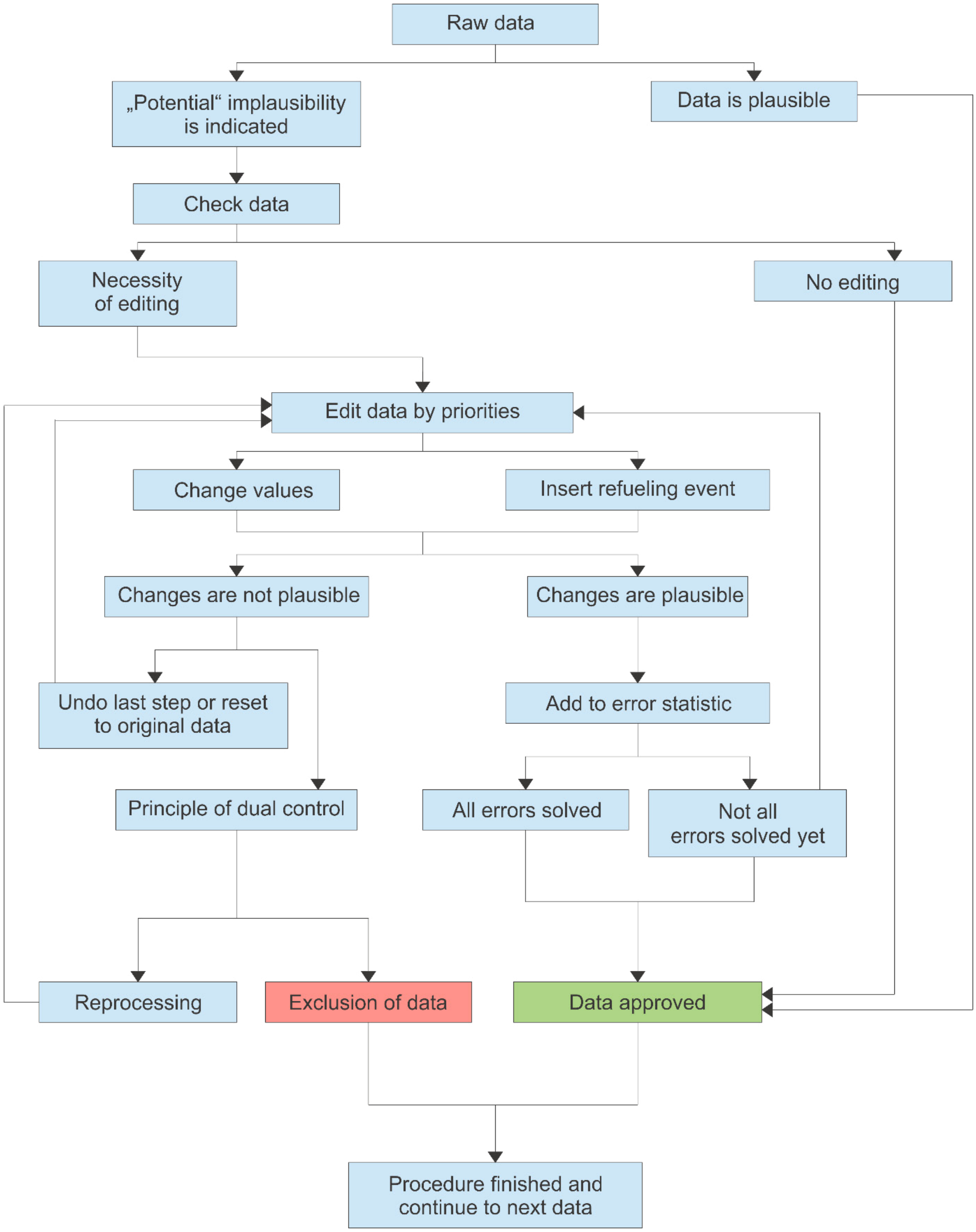

Figure 3: Workflow of the data-checking process on mileage and fuel consumption data in the MOP

Detected Errors

In 2019, 1,129 inconsistencies were detected in the dataset. Contradictory initial fuel levels caused 78% of these inconsistencies (e.g. there is not enough volume in the tank for the added fuel. In the survey document, the tank level is marked graphically on a bar. However, this method to determine the tank level is highly prone to errors as the tank level is hard to read in the car and is therefore reported erroneously. In GraDiV, we readjust the tank's fuel amount at the beginning/end of the reporting period to address this kind of error.

The use of the visualization tool to check for implausibilities in the reported refueling events provides benefits: As noted in the survey on everyday travel behavior, the checking staff can work faster and more efficiently. Even though we cannot compare the time saved before and after implementing the tool directly, we assume that the time effort is reduced by about 50 %.

5. Discussion and Conclusion

The idea behind the data-checking processes is to provide data free of implausibilities and missing data. Consequently, insufficient data must be identified and corrected. However, the guiding principle should remain to edit the raw data only as much as necessary and as little as possible. In this article, we provide insights into the data-checking processes of the MOP using data visualization tools (GraDiV) to identify various types of errors. We show that the assessment of reported travel behavior by humans is strongly supported by data visualization.

The outcome of our processes results in plausible and complete data. The predefined checks and graphically highlighted areas in the GraDiV tools allow for structured and replicable procedures easing the checking staff's work. The update of the existing tool using the experiences made with former software solutions has paid off for the data-checking process: The tool reduces the total workload of the checking staff. As a further benefit, the automatic calculation of fuel consumption between refueling events and fuel capacity before/after each refueling event minimizes the time for data-checking.

Nevertheless, it is necessary to train the checking staff and teach them how to use and interpret the data and use the different information levels provided (e.g. comparison with other persons, intraindividual comparisons with the previous year, etc.). The checking staff learns to recognize specific patterns and repetitive behavior through the training, thus making the checks more efficient and replicable.

From a practical perspective, the benefits of the various functionalities of the GraDiV tools are obvious. Furthermore, additional scientific advantages exist: the checking staff gains more profound knowledge on travel behavior in all its facets, enabling them to better understand and analyze the data.

Institutions that process survey data have to deal with deficient and missing information in the data. We recommend paying more attention to processes that improve data quality to develop a best practice and ensure comparability between studies. Besides applying rule-based algorithms, the application of visualization tools can be regarded as a practical approach. In principle, GraDiV is suitable for any review of diary-based travel surveys. This applies to reference date surveys (one day), surveys with a more extended survey period (e.g. a week or even more), and cross-sectional and longitudinal surveys. Even though more and more data are now collected automatically (e.g. GPS tracking), the issue of data post-processing still remains.

In the future, we also see a need and scope for further research in machine learning algorithms. The continuous application of the plausibility tool for several years allows for the application of machine learning algorithms. For this purpose, both the raw and the processed data are available. Thus, algorithms can be taught how irregularities and certain kinds of errors are identified and how human intelligence has corrected them. This provides unique data for training algorithms. The visualization of trips and activities of people has already been used to classify participants based on their behaviors using machine learning. An analysis by von Behren et al. (2020) shows that the GraDiV images of travel behavior as standardized pictures are well suited for machine processing.

Lastly, it should be mentioned that many errors can easily be anticipated and suppressed when designing a survey. By using online surveys and apps, implausible information can be avoided by providing information to the participant. Nevertheless, checking data quality and editing, especially missing data, will still be essential in future surveys – even when smartphones collect data automatically. For this case, GraDiV can also be regarded as an efficient approach to increase the data's reliability.

6. Acknowledgements

This paper presents analyses of the German Mobility Panel funded by the German Federal Ministry for Digital and Transport.

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