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# Workshop synthesis: Data Fusion - Generating More Than a Sum of Parts

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**Abstract**

This report summarizes the insights from a workshop conducted during the 12th International Conference on Transport Survey Methods focusing on data fusion. The workshop discussion and the presentations illustrated that data fusion comes in many ways utilizing various data and methodologies. While much of the academic literature and practical applications of data fusion in transport apply to travel demand modelling, fusion in the context of travel survey data production is still in its infancy. Despite data fusion's acknowledged potential, a reason for this hesitancy is a lack of quality standards. The report recommends future research to improve knowledge about the suitability of data and methodologies for fusion and the development of respective standards. This will be necessary to convince stakeholders that the quality of fused data is not inferior to any single data source, be it travel survey data or, e.g. mobile phone data.



*Keywords:* travel survey; travel data; data fusion; imputation; weighting; data correction; big data

## 1. Introduction

This report presents the finding of a workshop on data fusion held at the 12th ISCTSC conference in Vimeiro, Portugal, in March 2022. The workshop started with five presentations that related to (*i*) validation of travel survey data, (*ii*) tabulation of annual statistics, and (*iii*) augmentation of traditional surveys with "big" data streams (see section 2). The workshop was then continued by an in-depth discussion of data fusion, primarily in the context of travel survey data production.

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Emerging new data sources, ranging from sensor data over smart card data to mobile phone data, have inspired a range of possible data fusion approaches in the context of transport data (Cherchi and Bhat, 2018). Many of these approaches aim at harnessing data fusion possibilities in the context of modelling, specifically travel demand modelling (International Transport Forum, 2021) or in the context of intelligent transport systems (El Faouzi et al., 2011). This workshop report concentrates on data fusion in the context of travel survey data production. Data fusion has long been part of travel and traffic survey data production, employing relatively conventional fusion techniques such as weighting or imputation (Armoogum and Madre, 1998). However, relative to the increased attention to data fusion in recent years – specifically fueled by data fusion in the context of travel demand modelling (Brederode et al., 2019) – data fusion involving emerging or big data is far less common in the context of travel survey data production. Nevertheless, - as underlined in earlier workshops in the ISCTSC conference series (Cherchi and Bhat, 2018) - there is a great potential for data fusion to contribute to higher travel survey data quality. Fusion may reduce respondent burden and thus make the fieldwork of data production leaner. At the same time, it improves the richness and quality of the resulting data. This workshop report will illustrate this potential, show the specific barriers to data fusion in the context of data production, and point to challenges that need to be addressed to overcome these barriers.

In this report, the term data production refers to the generation of the data raw material as obtained from surveys before moving on to further usages such as statistical analyses or modelling. There is often no clear boundary between travel survey data production (including survey design and planning, fieldwork and post-processing of the data) and subsequent use of the data, e.g. in travel demand modelling. However, survey data production – generating a survey data set and usually a report accompanying the survey – is typically a separate project from subsequent data uses. This paper concentrates on data fusion in the context of survey data production (i.e. the left side of Figure 1), not in the context of modelling (i.e. the right side of Figure 1).

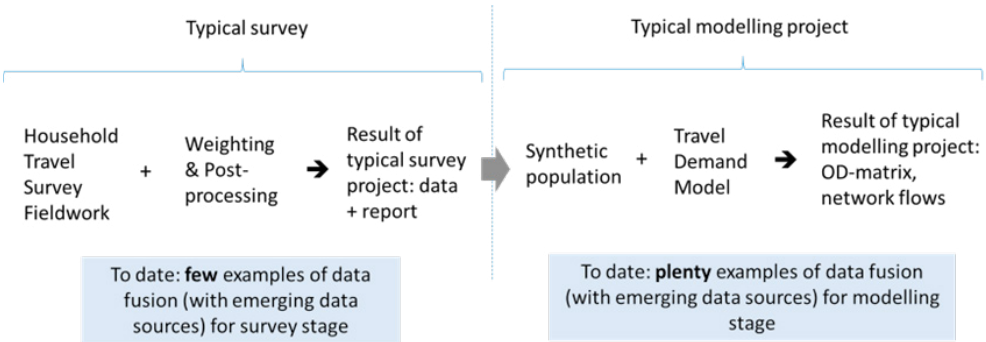


Fig. 1. Visualization of the scope of survey data production and subsequent data usage, e.g. modelling

As for possible data sources and fusion techniques, we concentrate on a few prototypical examples. This is because it is futile to comprehensively account for the seemingly endless options of combining data sources – the range of which is partly exemplified by the papers presented in the workshop, see below. We will use the terms “base data” to refer to the original data set, which is typically based on a survey, and the term “auxiliary data” to refer to external data which is used in the fusion procedure in addition to the base data in order to improve the latter. To illustrate the discussion in this report, we will primarily refer to a typical example from a household travel survey data set as an example for the base data. In addition, we will refer to the typical data format consisting of rows (i.e. observations) and columns (i.e. variables). As for auxiliary data, specific attention is given to mobile phone and smartphone data. This is sometimes promoted as a possible alternative to conventional travel survey data or as a specifically rich data source that may be combined with travel survey data (Bonnel et al., 2018).

## 2. Data fusion in the context of travel survey data production: concept and examples

Establishing a useful notion of the term “data fusion” in the context of survey data production was one of the first objectives of the workshop. Very general definitions of data fusion can be found in the literature, basically referring to linking or combining different sources of data (Castanedo, 2013). Therefore, we will not introduce a definition but present our notion of data fusion tailored to the context of survey data production, attempting to make data fusion more concrete and tangible. In this paper, we will use the term data fusion to refer to the combination of information from different sources to generate data that fulfils predefined conditions (Figure 2). Typically, the objectives of data fusion in the context of data production fall into three categories; data fusion aims to:

1. correct the base data. This refers to checking and improving the quality of the base data. Combinations with other data sources may refer to the use of external data, e.g. to check mode availability on specific routes or travel speeds with specific modes. Another very common example of data fusion is the use of external data to impute missing values. In the context of a conventional data set, this means checking, correcting or complementing individual values in cells in pre-existing rows and columns of a base data set.
2. increase the coverage of the base data. This refers to extending the base data vertically, e.g. by weighting or actually adding rows to the data set. Hence, conventional weighting is a form of well-established data fusion as long as it involves external data, for example, when generating post-stratification weights using external marginal distributions.
3. increase the richness of the base data. This refers to extending the base data horizontally, usually by adding new columns to the data set. A typical example of this type of data fusion is adding new variables to a data set which have not been part of the base data and are not generated by solely recombining variables contained in the base data (Eisenmann and Kuhnimhof, 2018).

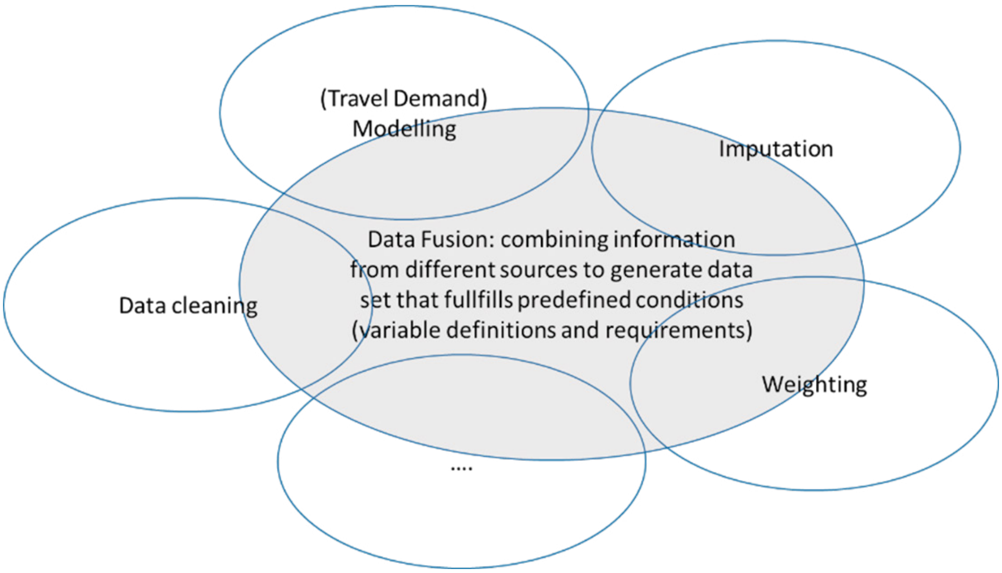


Fig. 2. Our notion of data fusion and examples of data fusion in the context of travel survey data production

Real-world data fusion examples recombine these core objectives of data fusion in countless variations. Even the objectives of complex data fusion procedures broadly fall into these three categories. The papers presented in the workshop illustrated this. While they varied considerably with regard to the data and methods used, they all had in common that they combined data from different sources (often, the boundaries between base data and external data were blurred) and that the objectives of data fusion broadly aligned with the three categories above. von Behren et al. (2022) compared and combined data from different questionnaires and interviews with the same individuals to validate information obtained in a so-called "travel skeleton" survey that elicited general mode use and activity. This comparison aimed to establish the reliability of the travel skeleton data (i.e. aiming at correcting the base data) and identify potential options to extrapolate this data (i.e. aiming at increasing the coverage and richness of the travel skeleton data). Likewise, Gregg et al. (2022) combined survey data and mobile phone records using machine learning to reconstruct travel purposes and itineraries, i.e. to increase the richness of the base data. Three of the presented papers utilized data fusion to increase the spatio-temporal coverage of the original data. The German VKT model combines various data sources, including an up-to-date vehicle registry, total fuel use and total mileage data, as well as somewhat outdated vehicle mileage survey data, to produce detailed annual VKT and fuel consumption statistics (Eisenmann et al., 2022). This approach, hence, increases the temporal coverage of the base data by updating it through data fusion. Quite similarly, the updating procedure based on household survey data in combination with passive data streams presented by Deschaintres et al. (2022) also aimed at extending the temporal coverage of the base data. Instead, increasing the geographic resolution and coverage of existing data was the objective of the paper presented by Cirillo et al. (2022). They used vehicle positioning probe data and Bayesian hierarchical modelling to produce travel statistics for small areas.

The papers presented in the workshop gave an insight into the wide range of data, their potential combinations and the methods applied for fusing data. While the papers predominantly focused on further analysis and use of pre-existing base data, they inspired the discussion as to how such data fusion techniques could be used in the context of data production, which will be the focus of the remainder of this paper.

## 3. The potential of data fusion in the context of travel surveys

The focus of the workshop was on making data fusion an integral part of data production in order to make survey fieldwork leaner, i.e. with lower expenses and less respondent burden, and to compensate for this via combination with external data (Figure 3). Travel surveys around the globe are struggling with declining response rates, i.e. it is increasingly difficult to reach good coverage in terms of the observations representing the respective population (Prelipcean et al., 2018). Data fusion is regarded as one option to compensate for this, e.g. by identifying and compensating biases (e.g. weighting). At the same time, there is an increasing request for richer data, e.g. longitudinal data that procure deeper insights into individual behaviour. In essence, data analysts are after more variables per observation. Data fusion is seen as a possibility to obtain this data without actively eliciting this information from the survey respondent, which would increase respondent burden, further endangering response rates. Hence, data fusion is regarded as an option to make surveys leaner. In essence, this means asking fewer respondents less frequently and fewer questions – and compensating for the reduced amount of information from the survey itself through fusion.

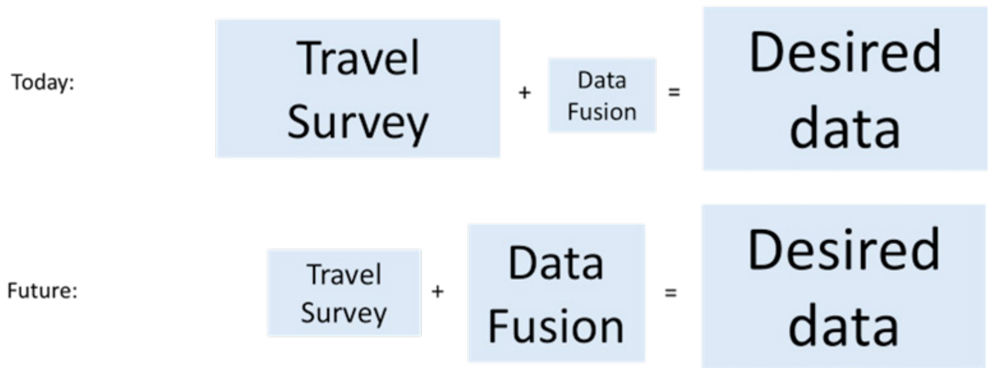


Fig. 3. Visualization of increased focus on data fusion in the context of data production

However, to transition from today's situation to a future situation with an increased focus on data fusion, substantial barriers must be overcome. In this context, academia often focuses on the technical and objective barriers. There is no question that the quality of auxiliary or external data, as well as the methods of data fusion, must be ensured. This may even extend to the ensuing methods of data analysis, for which today's standard approach of probabilistic statistics may not be a good option in the future (Kuhnimhof et al., 2018). These technicalities and objective criteria of the quality of data fusion and the resulting data are but one dimension of requirements which need to be fulfilled if we want to harness the envisioned potential of data fusion. The other dimension is subtler and more subjective: today, survey data is often regarded as "ground truth" by stakeholders and the public, even though experts acknowledge that survey data is also affected by bias and errors (Bonnel and Munizaga, 2018). This obviously raises the question if stakeholders trust data that results from fusion as much as they trust original data. This question applies to both survey data and other original data sources, even emerging ones such as mobile phone data. It is essential that fused data is regarded with the same level of trust as original survey data if data fusion - beyond today's established conventional methodologies - is to succeed in becoming an integral part of data production. To validate the quality of fused data and encourage trust, there must be established and transparent quality standards, which today are largely missing when it comes to data fusion beyond established methods. This points to one of the most relevant barriers when it comes to the large-scale practical implementation of data fusion in the context of travel data production for policy and planning, as will be discussed in Section 5 of this report.

## 4. The key examples of mobile phone data and OD-matrices

As shown in previous workshops of the ISCTSC conference (Bonnel and Munizaga, 2018), new data sources are emerging and allow for improved insights into mobility behaviour. This includes GPS data, mobile phone data, Wi-Fi and Bluetooth data, ticketing data, etc. Generally, mobile phone data are among the new data sources that have received the most attention in the context of data fusion in transport. Two types of mobile phone data are specifically interesting with regard to travel survey data production and were discussed in the workshop: (*i*) long-term individual smartphone location history data (i.e. GPS-based smartphone tracks) and (*ii*) aggregate mobile phone movement data (i.e. number of mobile phones or sim-cards moving between GSM-cells). These two represent the extremes of a spectrum of possibilities offered by mobile phone data, with (*i*) being very rich on the individual level and (*ii*) providing large amounts of aggregate data.

Mobile phone data type *i*, i.e. long-term, individual smartphone location history data based on GPS tracking may either be collected actively, i.e. through the use of a tracking app in the survey (Kuhnimhof et al., 2018). In that case, it is not of primary concern in the context of data fusion, because the tracking data actually is (at least part of) the original survey data. However, such data may also be made available through survey respondents or study participants who make their standard smartphone profile, e.g. Google timeline, available to data analysts (Zhang et al., 2022). Evidently, this type of data offers very detailed and rich insights into the behaviour of individuals and may profoundly enhance the understanding of specific facets of travel behaviour. This second approach generally provides a large quantity of data; however, the method requires the explicit consent of the respondents to acquire the data. It seems unlikely that more than just a tiny fraction of respondents would be willing to share their timeline data. Besides, statistical representativity can also be questioned in this scenario because people willing to collaborate are most likely not representative of the total population. Hence, this type of data yields very rich insights into the mobility of a very small and probably selective proportion of the population. This situation is likely to last unless data privacy regulations and concerns change substantially (which seems unlikely in the foreseeable future in most countries). Therefore, while this type of data is without a doubt interesting for academia, it seems unfit to produce representative travel data. This raises the question of to which degree such smartphone location history data can be fused with conventional travel survey data in order to extend conventional travel surveys horizontally, i.e. by imputing additional information which was not elicited in the original survey. Indeed, smartphone location data provides very little information except for a series of positions, and it can be tough to retrieve new variables from them (as an example, mode imputation can be challenging with GPS data). In order to develop and evaluate such methodologies, the properties of smartphone location history data, e.g. bias and selectivity must be understood. Since the use and analysis of such data are still in their infancy, the potential for data fusion in the context of large-scale representative travel data remains to be seen.

Mobile phone data type *ii*, i.e. aggregate mobile phone movement data, has been around for much longer. Its use – specifically the use of mobile phone or sim card movement OD-matrices – has been advocated for years, this data is on offer by mobile phone providers, and its use is proliferating in the context of travel demand modelling (International Transport Forum, 2021). They can be derived from billing (call detail records) or from network signalling data, the latter providing even more observations (Fekih et al., 2019). Both of these ways to collect mobile phone data can provide a large number of data continuously and, most of all, passively. OD-matrices, which are a key data format for transport planning, have, until a few years ago, mostly been generated by intricate modelling techniques based on the input from conventional travel surveys. In recent years mobile phone data has been promoted to supplement or even replace travel surveys in the context of generating OD-matrices. At first sight, given the seemingly complete coverage of the population with mobile phones and the pervasiveness of their presence in travel behaviour, there seems to be a strong point for this claim. However, there are open questions, e.g. relating to distinguishing mobile phone movements from person movements (one person may carry several sim cards), or the proportion of the market covered by any single mobile phone provider or the overlap of these market shares, respectively. Cools et al. (2010a) report an illustrative example that shows the limits of simply upscaling even unbiased OD-matrix subsamples by showing that even with a huge market share, if simple redressment weights are used, the quality of the expanded matrices is questionable: With a 50% random sample upscaled to population level, assuming only sampling error, the MAPE at a 589*589 OD-matrix for the Belgian population was 54.1%. Coverage errors as well as coverage and instrument biases are likely to harm further the quality of OD-matrices which are exclusively derived from mobile phone records. Besides, the precision of the travel derived from mobile phone data can depend on the intensity of the use made by the owner of the phone: the more the phone is used by its owner, the more signals it will emit (Bonnel et al., 2015).

Simply replacing conventionally generated survey data-based OD-matrices with mobile phone based OD-matrices does, hence, not make sense. However, the potential of mobile phone data in the context of travel data is undisputed. Cools et al. (2010b) provide an overview of possible combination methods to be used for validating and calibrating transport planning tools based on mobile phone data, and, as an example, Gong et al. (2021) present the validation of a travel demand model using mobile phone based OD-matrices. However, as can be seen, these examples again mostly relate to fusing mobile phone data into travel demand models. Direct combinations of travel survey data with mobile phone data with the intention to extend this data vertically (e.g. by weights for trips per distance class) or horizontally (e.g. by adding itinerary information to intercept survey data as in Gregg et al. (2022)) so far are exceptions. This raises the question of which barriers stand in the way of harnessing this potential.

## 5. Barriers and challenges for data fusion in the context of travel survey data

With regard to barriers that today stand in the way of broader application of data fusion in travel survey data production, the workshop discussion first pointed to a number of hard-fact and partly technical or methodological open questions:

- *Challenges regarding the suitability of auxiliary data*: Evidently, it is impossible to list all potential auxiliary data (specifically because available and suitable data sources may differ between locales, e.g. countries) and evaluate their suitability. However, it is also clear that specific overarching standards regarding the suitability of auxiliary data that do not exist today, can and must be established. Such standards, for example, concern the transparency on how the data was collected and clear definitions of the scope and coverage of the data (e.g. the question to which degree users of various mobile phones are contained in mobile phone data multiple times or not). It is also important to ensure the representativity of the population from which auxiliary data were provided (e.g. the representation of elderly people when considering mobile phone data) and that auxiliary data give enough information to be able to formulate strong hypotheses about people's travel.
- *Challenges regarding fusion methodologies*: As in the case of possible data sources, the potential bandwidth of fusion methods is enormous. Nevertheless, different categories of fusion technologies can be identified, e.g. falling into the three different objectives of improving the base data (see section 2). In addition, there are fusion techniques that are based on one-to-one linkage of disaggregate data (e.g. transferring information between statistical twins), while others are based on aggregate data linkage (e.g. weighting or imputing additional variables based on regression). Both go along with advantages and disadvantages. For example, one-to-one linkage using donor and acceptor observations may lead to more realistic variance patterns in the resulting data; however, it may also pretend an accuracy that does not exist in the data. This raises questions such as how twin-like statistical twins should actually be in order for one-to-one linkage to be a sensible approach or in which cases one should rather resort to aggregate data linkage. Again, reliable standards for data fusion techniques in the context of travel survey data should be developed to give guidance in the case of such challenges.
- *Challenges regarding analyses of fused data*: Fusion often changes the character of the original data such that fused data may not fulfil the prerequisites for the application of today's standard data analysis approaches based on probabilistic statistics. For example, fusion often impacts the variance structure of the resulting data. This raises the question of under which conditions and to which degree conventional statistics are applicable for the analysis of fused data or if analysts may have to resort to other analysis methods, such as machine learning.

Hence, for the analysis of fused data, new competencies on the side of the data analysts and guidance as to which analyses techniques are applicable will be needed.

Evidently, these challenges are closely interlinked and against the broad range of possible data and their combinations, establishing academic standards - even if only addressing the field of travel survey data production - is a substantial task. Accomplishing this task, however, will be necessary, as also discussed in the workshop. This is because such technical and scientifically acknowledged standards will form the foundation to tackle a problem, which in practice possibly even stands more in the way of applying data fusion than any of the challenges above: Convincing stakeholders that the quality of fused data is not inferior relative to the quality of any single original data source, be it travel survey data or, e.g. mobile phone data.

## 6. Recommendations and outlook

This report summarized key insights from a workshop conducted during the 12th International Conference on Transport Survey Methods focusing on data fusion in the context of travel survey data production. The workshop discussion and the presentations illustrated that data fusion comes in many different ways utilizing a broad range of data and methodologies. However, most established uses of data fusion concern subsequent uses of travel survey data, such as travel demand modelling. As for travel data production, examples of data fusion mostly concern relatively conventional data and methodology, such as weighting with official population statistics. While the potential of data fusion using emerging data sources and cutting-edge fusion techniques in the context of travel survey data production has been discussed for several years, their application is still in its infancy.

A reason for this hesitancy are the high-quality requirements that apply in the case of travel survey data production. Such data often form the basis for far-reaching and often cost-intensive policy or planning decisions, as in the case of new infrastructure. Hence, this data must be trustworthy and withstand legal disputes if policy or planning decisions are challenged. In this context, conventional travel survey data – like other measurements such as travel counts and passenger statistics – are often regarded as ground truth by stakeholders. Fused data must first earn this trust and confidence. Quality standards that comply with these high requirements have been developed and are established in the case of conventional data sources (such as population statistics) and conventional fusion techniques (such as weighting or imputation of missing values). However, to date, such quality standards are largely missing when it comes to emerging data sources or techniques.

While data fusion will continue to be broadly applied in subsequent data usages, we will not be able to harness the full potential of data fusion in order to improve our travel data scape unless the travel data academic community develops suitable quality standards. Hence, this report strongly recommends focusing research efforts on developing such standards to make data fusion applicable for data production in practice.

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