Institute of Transport Economics
Norwegian Centre for Transport Research

Valuation based on Big Data and revealed preference data

An assessment for Norwegian transport appraisal

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Short Summary

For several decades, stated preference (SP) studies have been the dominant method for transport valuation. However, there are many indications that revealed preference data is making a strong comeback due to access to Big Data and new analysis possibilities such as machine learning. In this report, we assess the capability of different RP data sources. We find that app-panel with GPS-tracking give the broadest and most precise basis for valuation. In order to accommodate current segmentation of unit values in Norwegian transport appraisal, one does, however, need to collect additional background surveys. The use of traditional travel surveys is also ranked high, in particular when synergies with the estimation of transport models can be realized.

Sammendrag

De siste tiårene har studier basert på såkalt «stated preference» (SP) vært den dominerende metode for å verdsette kvalitetsfaktorer som reisetid etc. i transportsektoren. Nå er det mye som taler for at «revealed preference» data kommer tilbake, ettersom en nå får tilgang på nye og store data og analysemetoder basert på maskinlæring. I dette prosjektet har vi vurdert mulighetene som ligger i ulike datakilder. Vi finner at data fra rekrutterte paneler som bruker applikasjoner med GPS-sporing gir det bredeste og mest presise grunnlaget for slik verdsetting. For å underbygge dagens segmentering av enhetsverdier i norske transportanalyser, trenger en imidlertid å samle inn bakgrunnsdata i egne undersøkelser. Bruk av tradisjonelle reisevaneundersøkelser har fortsatt stor verdi når disse også skal brukes til estimering av transportmodeller.

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Preface

This report documents an assessment of Big data and revealed preference (RP) data for valuation as input to Norwegian transport appraisal. The work is commissioned by the the Norwegian Public Roads Administration (NPRA), the Railway Directory, the Coastal Administration, Avinor, Nye Veier and Bane Nor, who also funded the last National Valuation study 2018-2019, a study that used stated preference (SP) as a main method.

Stefan Flügel has been the project leader at TØI. Christian Weber and Askill H. Halse contributed through the whole project with analysis and the planning and writing of the report. Ingunn O. Ellis has contributed to the report, in particular to the text regarding the RVU data.

We also acknowledge the contribution from Knut Veisten, who was part of the Delphi survey (alongside Flügel, Weber and Halse) and commented on parts of the report.

Oskar Kleven has been the contact person. We want to thank the clients for an interesting assignment and for good cooperation throughout the project.

As suggested by of the clients, we have written this report in English. A Norwegian summary is provided.

We want to thank Joachim Viktil (Rambøll) and Bendik Witzøe (NPRA) for their help with the purchase and analysis of the TomTom data described in section 5.2.

We also want to thank the participants of an internal workshop at TØI and other persons who directly or indirectly contributed to this work.

The report was quality ensured by Kjell Werner Johansen.

We also want to thank Trude Kvalsvik for help with the final editing and publication of the report.

Oslo, May 2022
Institute of Transport Economics

Bjørne Grimsrud	Kjell W. Johansen
Managing Director	Director of Research

Contents

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ENGLISH **Summary**

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For several decades, stated preference (SP) studies have been the dominant method for transport valuation. However, there are many indications that revealed preference (RP) data is making a strong comeback due to access to Big Data and new analysis possibilities such as machine learning.

In this report, we assess the capability of different RP data sources. We find that app-panel with GPS-tracking give the broadest and most precise bases for valuation. In order to accommodate current segmentation of unit values in Norwegian transport appraisal, one does, however, need to collect additional background surveys. The use of traditional travel surveys is also ranked high, in particular when synergies with the estimation of transport models can be realized.

Background and motivation

While SP studies build on an analysis of hypothetical choices in experimental settings without real-world consequences to the respondents, RP-choices are observed in real-world settings and therefore the preferred method to derive preferences. However, with RP data the researcher has little control over the data and little variation and/or high correlation in is a persistent challenge in RP-based estimation of unit values. This challenge can partly be overcome with larger data volume, which is more and more available due to the raise of Big data. Figure S1 summarises main advantages of RP data in general and Big Data in particular and how this may contribute to more valid and more up-to-date unit values for Norwegian appraisal.

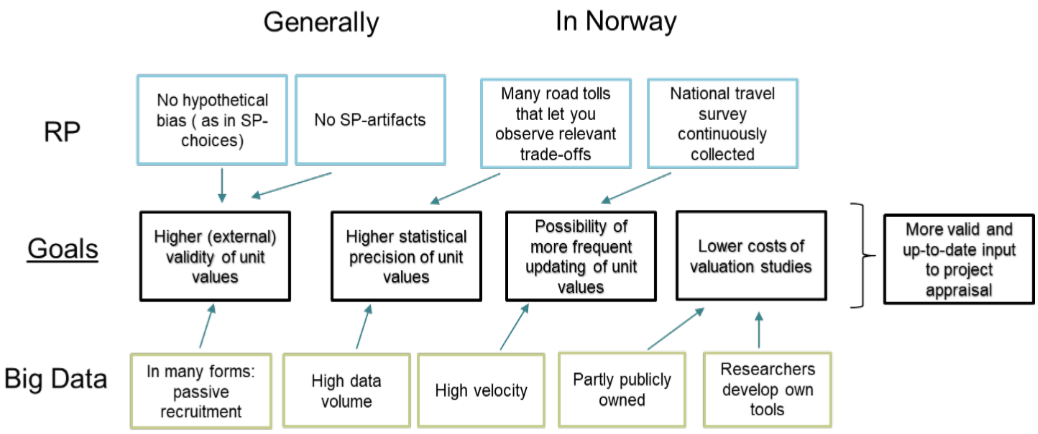

Figure S1: Overview over motivation of use of revealed preference (RP) data and Big Data for transport valuation.

Work tasks and method

The conclusions and recommendations in this report are based on:

1) A literature review on valuation based on RP/Big Data
2) A list up of possible data sources and a discussion of their relevance for valuation.
3) An assessment of relevant combination of data sources and unit values based on 19 different criteria. Scores are given on a scale of 1 to 5. The scoring was partly based on an internal Delphi survey.
4) A synthesis of the assessment in three groups of criteria: "Access and general quality", "Analysing opportunity for valuation" and "Flexibility, synergies and future perspective"
5) A practical description of three of the most promising approaches
6) A case study to illustrate some challenges of aggregated data sources

Data sources

For a data source to be relevant for valuation, the following need to apply:

1) The data need to be available in Norway or there needs to be clear path to how it can be made available.
2) The data set must give direct or indirect information on the behaviour of travellers, either in the form of individual choices or in the form of aggregated market shares.
3) The data set needs to enable the attachment of relevant and sufficiently precise attributes to the different alternatives in the choice set.
4) Some of the choices that are observed need to imply an actual trade-off between at least two attributes that are relevant for the underlying unit value. Attributes, like time and cost, can be positively correlated (and they often are in practice), but there needs to be some mechanisms (at least for a subset of choices) where variation in the data is invoked (e.g. through road tolls).Table S1 provides an overview of the included data sources and their main characteristics.

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Table S1: Overview of data sources.

Data source	Technology	(Assumed) data owner / access for researcher	(Assumed) level of aggregation of data	Most applicable choice context / unit value
National RVU	Traditional travel survey	Transport authority / free	Disaggregated (trips of single persons)	Mode choice / various
Mobile data	Call Detail Record via cell towers	Commercial providers as Telia / costly	Aggregated (BSU or routes)	Route choice (mainly long distance) / VTTS car
App panel with GPS-tracking	GPS/A-GPS , GNSS	Researchers / free access to own panels	Disaggregated (trips of single persons)	Mode- and Route choice / various
Automatic traffic counters (ATC)	Sensors (typically electrical induction)	NPRA / free	Aggregated (points)	Route choice / VTTS car
Toll transaction data	ANPR cameras and RFID devices	NPRA / free (limited as of today)	Disaggregated (cars over different points)	Route choice / VTTS car
Tracking data from commercial providers	Various (GPS, Navigation devices,..)	Commercial provider as TomTom or fitbit / costly	Aggregated (BSU or routes)	Route choice / VTTS car
Dedicated cameras and sensors	Various (ANPR, RFID, bluetooth tracking and magnetic sensors	Researchers / free access to self-installed hardware and data	Disaggregated (cars over different points)	Route choice / VTTS car
Mobility-as-a-Services ordering data	Stored data from apps	MaaS providers as Bolt or Ruter / unclear of today	Disaggregated (trips of single persons)	Various / VTTS (waiting time)
Automatic passenger counts (APC)	Various (camera technology, mobile phone tracking and/or light barriers)	PT providers / free (some restrictions)	Aggregated (station-pair/departure)	Submode-departure choice / crowding multiples
Camera-based crowd counts at stations	Cameras (supported by machine learning)	Researchers / free access to self-installed hardware and data	Aggregated (station/departure)	Wait for next departure at station / crowding multiples

Summary of assessment

Data access and general quality was assessed based on the following criteria:

- Access to relevant and updated RP data
- Resources required for data access and maintenance (high score for low resources needed by the executing body of the valuation study; original costs by others not included)
- Resources required for data processing (high score for low resources needed by the executing body of the valuation study; original costs by others not included)
- Data volume
- Coverage (high score if all of Norway is covered)
- Representativity

While the latter 3 criteria may depend on the unit value of interest, the total scores for this group of criteria is rather stable across different relevant unit values.

The criteria for Opportunities for analysis for valuation were:

- Observation of actual choices
- Quantification of attributes and costs of chosen alternative
- Identification/modelling of non-chosen alternatives (choice set)
- Quantification of attributes and costs of non-chosen alternative
- Variation and correlation in central attributes
- Possibility to control for other effects
- Possibility to segment (current segmentation)
- Possibility for combined RP-SP models and other advanced estimation methods

The last group of criteria encompasses flexibility, synergies and future perspective of the data sources. This group is assessed from a general perspective and not from the perspective of the researchers (as the two previous groups). The following criteria where included:

- Possibility to frequent and continuous data collections in future
- Possibility to segment results beyond current segmentation
- Synergies with transport models
- Other synergies
- Relevance for new trends/technologies

Figure S2 gives an overall ranking of the evaluated data types. The scores for opportunity for analysis for valuation apply to the unit value with the best score within each data type.

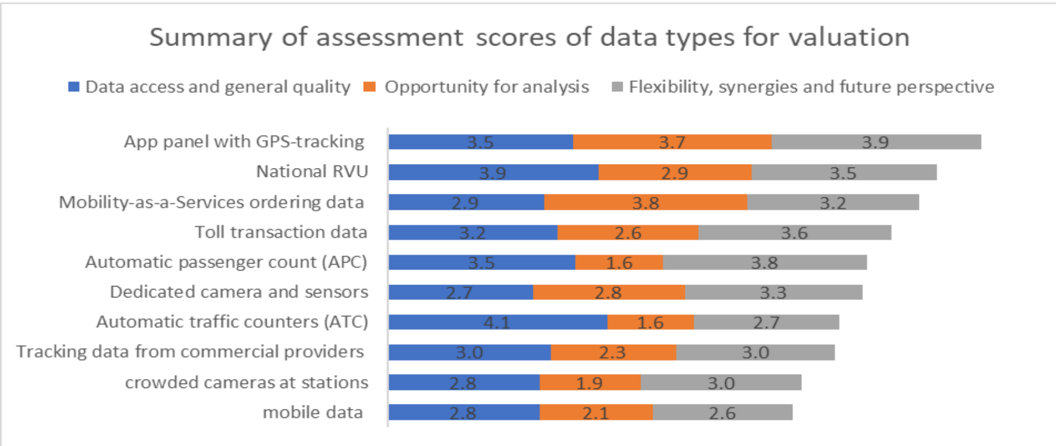


Figure S2: Overall ranking of RP-data types for valuation.

App panel with GPS-tracking is ranked highest overall.

The scores for Opportunities for analysis vary with the underlying unit values.

Besides the total scores, an important information is also how many unit values the data source in applicable for. Table S2 summaries our findings.

Table S2: Number of applicable unit values and range of total scores for Opportunity of analysis for estimation of unit values

Data source	Number of unit value data is applicable*	Total score	Main advantage	Main disadvantage
National RVU	6	2.2- 2.9	covers current requirement for segmentation	imprecise spatial information
mobile data	2	1.7-2.1	somewhat better control over routes compared to ATC, at least for long distance	little control and possibility for segmentation; works poorly for short distance routes
App panel with GPS-tracking	10	3.3-3.7	detailed information on routes	trip purpose unreliable observed
Automatic traffic counters (ATC)	1	1.6		routes not directly observed
Toll transaction data	2	2.6	can distinguish car types	works only in networks that contain road tolls
Tracking data from commercial providers	2	2.1-2.3	better control over route than mobile data and ATC	little background information
Dedicated cameras and sensors	4	2.7-2.9	good control over routes given good sufficient coverage of cameras	trip purpose not observed
Mobility-as-a-Services ordering data	2	3.5-3.8	direct and precise information on attribute values	trip purpose not observed, open the app likely endogenous
Automatic passenger counts (APC)	1	1.6		OD not directly observed
crowded cameras at stations	1	1.9		Works only under specific conditions

Illustrations and case study

The report also contains a more practical description of three of the most promising approaches (National RVU, Fotefar, which is a upcoming GPS-app tracking software, and toll transaction data) as well as a case study using aggregated data sources (traffic counts, mobile data and data from TomTom). The latter illustrates some of the practical difficulties in using aggregated data to derive unit values.

Conclusion and recommendation

Below we summarise our main conclusions:

1) As of today, travel surveys such as **national RVU** are the most relevant data source with regard to the current segmentation of unit values

which require information about travel purposes. There are large potential synergies with transport models and one should consider aligning the next RTM estimation with the next valuation study. In this connection, it may be appropriate to move away from the current RVU, and rather design a more tailored survey that is better suited for both demand modelling and valuation.

2) **Data from apps that can track individuals** with GPS or other high resolution/frequency sensors score overall best in our assessment. The ability to add background information is important. This may require additional data collection, for instance in form of surveys.

3) A combination of surveys (and/or register data) and GPS tracking is considered the best option and something that is recommended to work towards.

4) **Aggregated data** (e.g. counting data on roads and public transport) place great constraints on analysis opportunities and will hardly be sufficient for national unit values given requirements coverage and in the current segmentation. That said, it can – based on appropriate case studies – help to validate the absolute level of the value of time (VTTS).

5) Aggregated **mobile data** provides better analysis options compared to counting data, at least for intercity travel, but is quite expensive to get access to. As other aggregated data sources it has clear limitations compared to more disaggregated data sources.

6) **Toll transaction data that tracks individual cars** will be able to provide information of route choice of individuals or groups in areas with a good coverage of road tolls and there are different possibilities to add individual background variables. Such data would in most cases not be completely anonymous, but access to non-anonymous data for research purposes would most likely be feasible under the current data protection legislation. However, facilitating access to data would require some goodwill and effort of the owners of the data. A more flexible (but more expensive) alternative to this data is to set up d**edicated cameras for automatic number plate recognition** (ANPR).

7) **Aggregated App-data from commercial enterprises** can also be a promising alternative. NPRA has access to aggregated tracking results from e.g. TomTom, a data source which could be utilized more for studying route choice behaviour, e.g. at toll roads across the country. In order to use TomTom data for research, access to more information about data collection and data processing, and the possibility the share this information with the public, are crucial. There are currently also major limitation in sharing data and publishing results from data analysis.

8) Most data sources mentioned under 4) – 7) have a fundamental advantage in their passive recruitment. The data sources are therefore interesting for the quality assurance of survey and app-based studies where unobservable factors can affect the level of the VTTS due to sample selection bias. That said, there can also be some biases in the sample of mobile companies and app-data providers.

9) A disaggregated data source with great potential are **MaaS ordering data** (e.g. from raid-hailing services). It is currently limited in access and application. In Norway studying choices/preference for micro-mobility seems most applicable. This type of data might also be made available via future versions of more traditional PT apps (e.g. via a future version of the Ruter-app that may let travellers pick, order and pay for all available transport solutions).

We see three approaches for the next valuation study. They are given below in ranked order.

1) **GPS-tracking data plus background surveys.** The recruitment should come from a combination of large (existing) samples or – preferably – the population register. Economic incentives should be given for donating tracking data to the project as this is likely to attract a broader sample and can therefore reduce the danger of sample selection biases. From a modelling perspective, combined mode and route choice models are likely to give the best and broadest basis for unit value estimation. The background survey should include questions on mode, car type and ticket type availability and include information about the location of home, work and other points of interest of respondents such that trip purpose can be derived from the spatial information in the GPS data. In addition, small SP experiments could be included in the background survey for cross-validation and for estimation of unit values that may be difficult to estimate from RP data.
2) **National RVU or – preferable – a tailored travel survey in a joint estimation with the RTM model.** Compared to suggestion (1.), this approach puts less weight on precise data and emphasizes consistency and synergies with transport models. The unit values would be derived from the mode choice utility function of the mode/destination choice models that are part of the RTM model system. Fitting route choice models in the network assignment tool (e.g. CUBE) against aggregated data sources can in addition support the estimation/recommendation of unit values. It is highly recommended that spatial information from the travel survey data is provide with 8 digit BSU ("grunnkrets") codes throughout (i.e. annul the current practice of providing BSUs with less than 100 inhabitants with 6 digit codes). With that, the level of precision will still be far below GPS-tracking, but should be acceptable within this approach.
3) A third approach would be to **keep the stated preference** approach. In this case, we would recommend **to use several well-crafted RP case studies to validate/adjust the overall level of VTTS**. Combined RP-SP models would be recommended in order to utilized the advantages of both data types. In this connection it would be preferable to recruit part of the SP sample from the areas where the RP case studies are conducted.

Transportøkonomisk institutt
Stiftelsen Norsk senter for samferdselsforskning

NORSK Sammendrag

Verdsetting basert på stordata og avslørte preferanser

En vurdering av muligheter for analyser innenfor transport

TØI rapport 1882/2022 • Forfattere: Stefan Flügel, Christian Weber, Askill H. Halse, Ingunn O. Ellis • Oslo 2022 • 90 sider

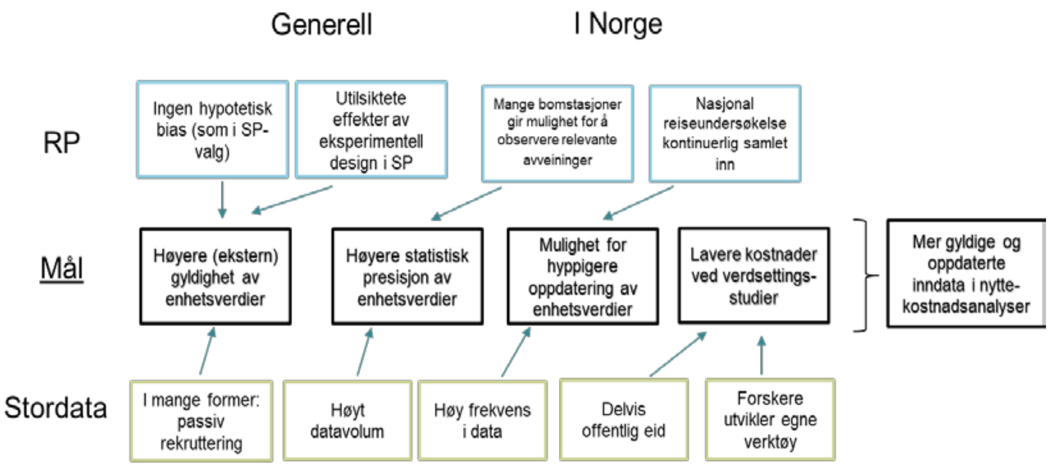
I flere tiår har uttalte («stated») preferanser (SP) vært den dominerende metoden for verdsetting innenfor transport. Det er imidlertid mye som tyder på at avslørte («revealed») preferanser (RP) gjør et sterkt comeback på grunn av tilgang til stordata og nye analysemuligheter som maskinlæring.

I denne rapporten vurderer vi muligheter som ligger i ulike RP-datakilder. Vi finner at data med GPS-sporing gir det bredeste og mest presise grunnlaget for verdsetting. For å kunne ivareta dagens segmentering av enhetsverdier, må man imidlertid samle inn ytterligere bakgrunnsdata. Bruken av tradisjonelle reisevaneundersøkelser er også rangert høyt, spesielt når synergier med estimering av transportmodeller kan realiseres.

Bakgrunn og motivasjon

Mens SP-studier bygger på en analyse av hypotetiske valg i eksperimentelle omgivelser uten reelle konsekvenser for respondentene, blir RP-valg observert i virkelige omgivelser og er derfor den foretrukne metoden for å utlede preferanser. Men med RP-data har forskeren liten kontroll over dataene, og liten variasjon og/eller høy korrelasjon er en vedvarende utfordring i RP-basert estimering av enhetsverdier. Denne utfordringen kan delvis overvinnes med større datavolum, som blir mer og mer tilgjengelig på grunn av økningen av stordata.

Figur S1 oppsummerer hovedfordeler med RP-data generelt og med stordata, og illustrerer hvordan dette kan bidra til mer valide og mer oppdaterte enhetsverdier for analyser innenfor transport, deriblant nytte-kostnadsanalyser.



Figur S1: Oversikt over motivasjon for bruk av revealed preference (RP) data og stordata for transportrelatert verdsetting

Arbeidsoppgaver og metode

Konklusjonene og anbefalingene i denne rapporten er basert på:

1) En litteraturgjennomgang om RP/stordata- basert verdsetting.
2) En liste over mulige datakilder og en diskusjon av deres relevans for verdsetting.
3) En vurdering av relevant kombinasjon av datakilder og enhetsverdier basert på 19 ulike kriterier. Poeng gis på en skala fra 1 til 5. Poengsummen er delvis basert på en intern Delphi-undersøkelse.
4) En syntese av vurderingen i tre grupper av kriterier: «Tilgang og generell kvalitet», «Analysemulighet for verdsettelse» og «Fleksibilitet, synergier og fremtidsperspektiv».
5) En praktisk beskrivelse av tre av de mest lovende tilnærmingene.
6) En casestudie for å illustrere noen utfordringer ved aggregerte datakilder.

Tabell S1 gir en oversikt over de inkluderte datakildene og noen sentrale egenskaper.

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Tabell S1: Oversikt over datakilder.

Datakilde	Teknologi	(Antatt) eier av data / tilgang for forskerne	(Antatt) aggregeringsnivå	Mest egnet valgkontekst / enhetsverdi
Nasjonal RVU	Tradisjonell reisevaneundersøke lse	Transport- etatene / gratis	Disaggregert (enkeltreiser for personer)	Transportmiddelval g / diverse
Mobildata	"Call Detail Record" via mobilmaster	Kommersielle tilbydere som Telia / kostbar	Aggregert (grunnkrets eller ruter)	Rutevalg (hovedsakelig lange distanser) / VTTS bil
App panel med GPS-sporing	GPS/A-GPS , GNSS	Forsker / fri tilgang til egne paneler	Disaggregert (enkeltreiser for personer)	Transportmiddel- og rutevalg / diverse
Trafikktelledata	Sensorer (typisk elektrisk induksjon)	NPRA / fri	Aggregert (punkter)	Rutevalg / VTTS bil
Bompasserings- data	ANPR kamera and RFID («bombrikke»)	NPRA / fri (begrenset tilgang per i dag)	Disaggregert (biler over flere punkter)	Rutevalg / VTTS bil
Sporingsdata fra kommersielle tilbydere	Diverse (GPS, navigasjonsverktøy, ..)	Kommersielle tilbydere som TomTom eller Fitbit / kostbar	Aggregert (grunnkrets eller ruter)	Rutevalg / VTTS bil
Egeninstallerte kamera og sensorer	Diverse (ANPR, RFID, blåtann og magnetiske sensorer	Forskerne / fri tilgang til egeninstallerte maskinvare og data	Disaggregert (biler over flere punkter)	Rutevalg / VTTS bil
Mobility-as-a-Service bestillingsdata	Lagrete data fra apper	MaaS tilbydere som Bolt eller Ruter / uklar per i dag	Disaggregert (enkeltreiser for personer)	Diverse / VTTS (ventetid)
Passasjertellinger	Diverse (kamerateknologi, mobilsporing og/eller lysbarrierer)	Kollektiv- selskapene / fri (noen restriksjoner)	Aggregert (snitt/avgang)	Valg av driftsart/avgang / trengselsfaktorer
Kamerabaserte tellinger ved stasjoner	Kamera (underbygd av maskinlæring)	Forskerne / fri tilgang til egeninstallerte maskinvare og data	Aggregert (stasjon/avgang)	Vente på neste avgang ved stasjon / trengselsfaktorer

Sammendrag av evalueringen

Datatilgang og generell kvalitet ble vurdert basert på følgende kriterier:

- Tilgang til relevante og oppdaterte RP-data
- Ressurser som kreves for datatilgang og vedlikehold (høy poengsum for lave ressurser som kreves av det utførende organet for verdsettingsstudien; opprinnelige kostnader fra andre ikke inkludert)
- Ressurser som kreves for databehandling (høy poengsum for lave ressurser som kreves av det utførende organet for verdsettingsstudien; opprinnelige kostnader fra andre ikke inkludert)
- Datavolum
- Dekning (høy poengsum hvis hele Norge er dekket)
- Representativitet

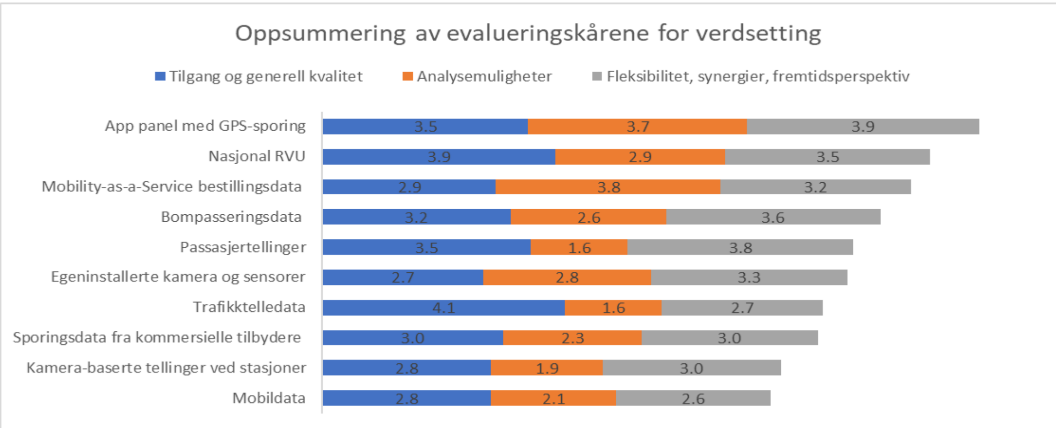
Mens de tre sistnevnte kriteriene kan avhenge av enhetsverdien, er den totale poengsummen for denne gruppen av kriterier ganske stabil på tvers av ulike relevante enhetsverdier av samme datakilde.Kriteriene for muligheter for analyse for verdsetting var:

- Observasjon av faktiske valg
- Kvantifisering av attributter og kostnader ved valgt alternativ
- Identifisering/modellering av ikke-valgte alternativer (valgsett)
- Kvantifisering av attributter og kostnader ved ikke-valgt alternativ
- Variasjon og korrelasjon i sentrale attributter
- Mulighet for kontroll for andre effekter
- Mulighet for segmentering (nåværende segmentering)
- Mulighet for kombinerte RP-SP modeller og andre avanserte estimeringsmetoder

Den siste gruppen av kriterier omfatter fleksibilitet, synergier og fremtidsperspektiv for datakildene. Denne gruppen vurderes ut fra et generelt perspektiv og ikke fra forskernes perspektiv (som de to foregående gruppene). Følgende kriterier var inkludert:

- Mulighet for hyppige og kontinuerlige datainnsamlinger i fremtiden
- Mulighet for å segmentere resultater utover dagens segmentering
- Synergier med transportmodeller
- Andre synergier
- Relevans for nye trender/teknologier

Figur S2 gir en samlet rangering av de evaluerte datatypene. Skårene for mulighet for analyse for verdsetting gjelder enhetsverdien med best score innenfor hver datatype.



Figur S2: Overordnet rangering av RP-datakilder for verdsetting.

App-panel med GPS-sporing er rangert høyest totalt sett.

Poengsummene for muligheter for analyse varierer med de underliggende enhetsverdiene.

En annen viktig informasjon er hvor mange enhetsverdier datakilden kan brukes for. Tabell S2 oppsummerer funnene våre.

Tabell S2: Antall relevante enhetsverdier og spenn i total skår for analysemulighet for estimering av enhetsverdier.

Datakilde	Antall relevante enhetsverdier *	Total skår	Hovedfordel	Hovedulempe
Nasjonal RVU	6	2,2- 2,9	Dekker dagens krav til segmentering	Unøyaktig steds-festing
Mobildata	2	1,7-2,1	Noe bedre kontroll over ruter sammenlignet med telledata, i alle fall for lange reiser	Lite kontroll og muligheter for segmentering, fungerer dårlig for korte distanser
App panel med GPS-sporing	10	3,3-3,7	Detaljert informasjon om ruter	Reisehensikt upålitelig observert
Trafikktelledata	1	1,6		Ruter ikke direkte observert
Bompasseringsdata	2	2,6	Kan skille biltyper	Fungerer bare i nettverk med mange bomstasjoner
Sporingsdata fra kommersielle tilbydere	2	2,1-2,3	Bedre kontroll over ruten enn med telledata og mobildata	Lite bakgrunns-informasjon
Egeninstallerte kamera og sensorer	4	2,7-2,9	Bra kontroll over ruter hvis god dekning av kameraene	Reisehensikt ikke observert
Mobility-as-a-Service bestillingsdata	2	3,5-3,8	Direkte og presis informasjon om attributtverdier	Reisehensikt ikke observert, bruk av app muligens endogent
Passasjertellinger	1	1,6		OD-relasjoner er ikke direkte observert
Kamerabaserte tellinger ved stasjoner	1	1,9		Fungerer kun under spesielle forhold

Illustrasjons- og casestudie

Rapporten inneholder også en mer praktisk beskrivelse av tre av de mest lovende tilnærmingene (nasjonal RVU, Fotefar, som er en kommende GPS-app-sporings-programvare, og bompasseringsdata) samt en casestudie ved bruk av aggregerte datakilder (trafikktellinger, mobildata og data fra TomTom). Sistnevnte illustrerer noen av de praktiske vanskelighetene ved å bruke aggregerte data for å utlede enhetsverdier.

Konklusjoner og anbefalinger

Nedenfor oppsummerer vi hovedkonklusjonene våre:

1) Per i dag er reiseundersøkelser som **nasjonal RVU** den mest relevante datakilden med tanke på dagens segmentering av enhetsverdier som krever informasjon om reiseformål. Det er store potensielle synergier med transportmodeller og man bør vurdere å samkjøre neste RTM-

estimering med neste verdsettingsstudie. I den forbindelse kan det være hensiktsmessig å gå bort fra dagens RVU, og heller utforme en mer skreddersydd undersøkelse som egner seg bedre både for etterspørsels-modellering og verdsetting.

2) Data fra apper som kan **spore individer med GPS** eller andre høyoppløse-lige og høyfrekvente sensorer scorer totalt sett best i vår vurdering. Mulighet for å legge til bakgrunnsinformasjon er viktig. Dette kan kreve ytterligere datainnsamling, for eksempel i form av spørreundersøkelser.
3) **En kombinasjon av spørreundersøkelser (og/eller registerdata) og GPS-sporing anses som det beste alternativet og noe som anbefales å jobbe mot.**
4) **Aggregerte data** (f.eks. trafikktelledata og passasjertelledata) legger store begrensninger på analysemuligheter og vil neppe være tilstrekkelig for nasjonale enhetsverdier gitt kravene til dekning og segmentering. Når det er sagt, kan det – basert på passende casestudier – bidra til å validere det absolutte nivået på tidsverdien (VTTS).
5) **Aggregerte mobildata** gir bedre analysemuligheter sammenlignet med telledata, i hvert fall for lange distanser, men er ganske dyrt å få tilgang til. Som andre aggregerte datakilder har mobildata klare begrensninger sammenlignet med mer disaggregerte datakilder.
6) **Bompasseringsdata** som sporer biler vil kunne gi informasjon om rutevalg for enkeltpersoner eller grupper i områder med god dekning av bomsta-sjoner. Det er ulike muligheter for å legge inn individuelle bakgrunns-variabler. Slike data vil i de fleste tilfeller ikke være helt anonyme, men tilgang til ikke-anonyme data for forskningsformål vil mest sannsynlig være mulig under gjeldende personvernlover. Å lette tilgangen til data vil imidlertid kreve noe velvilje og innsats fra eierne av dataene. Et mer fleksibelt (men dyrere) alternativ til disse dataene er å sette opp **egne kameraer for automatisk nummerskiltgjenkjenning** (ANPR).
7) **Aggregerte App-data fra kommersielle** virksomheter kan også være et lovende alternativ. Statens vegvesen har tilgang til aggregerte sporings-resultater fra f.eks. TomTom, en datakilde som kan brukes mer enn i dag for å studere ruteatferd, f.eks. ved bompenger over hele landet. For å bruke TomTom-data til forskning er tilgang til mer informasjon om datainnsamling og databehandling, og muligheten å dele denne informasjonen i offentlige rapporter/artikler er avgjørende. Det er for tiden også store begrensninger i å dele data og publisere resultater fra dataanalyse.
8) De fleste datakilder nevnt under 4) – 7) har en grunnleggende fordel i sin **passive rekruttering**. Datakildene er derfor interessante for kvalitets-sikring av undersøkelser og app-baserte studier der uobserverbare faktorer kan påvirke nivået på VTTS på grunn av utvalgsskjevhet. Når det er sagt, kan det også være noen skjevheter i utvalget hos mobilselskaper og app-dataleverandører.
9) En disaggregert datakilde med stort potensial er **MaaS-bestillingsdata** (f.eks. fra raid-hailing-tjenester). Slike data er for øyeblikket begrenset i tilgang og anvendelse. I Norge virker det mest aktuelt å studere valg/-

preferanser for mikromobilitet. Denne typen data kan også gjøres tilgjengelig via fremtidige versjoner av mer tradisjonelle kollektiv-apper (f.eks. via en fremtidig versjon av Ruter-appen som kan la reisende velge, bestille og betale for alle tilgjengelige transportløsninger).

Vi ser tre tilnærminger for neste verdsettingsstudie. Disse er gitt nedenfor i rangert rekkefølge.

1) **GPS-sporingsdata pluss bakgrunnsundersøkelser**. Rekrutteringen bør komme fra en kombinasjon av store (eksisterende) utvalg eller – helst – Folkeregisteret. Det bør gis økonomiske insentiver for å donere sporings-data til prosjektet, da dette sannsynligvis vil tiltrekke seg et bredere utvalg og derfor kan redusere faren for utvalgsskjevheter. Fra et model-leringsperspektiv vil kombinerte transportmiddelvalg- og rutevalgmodel-ler sannsynligvis gi det beste og bredeste grunnlaget for estimering av enhetsverdier. Bakgrunnsundersøkelsen bør inkludere spørsmål om tilgang til transportmiddel, biltype og billettype og inkludere informasjon om stedsfesting av hjemmet, jobben og andre hyppige destinasjoner for respondentene slik at reiseformålet kan utledes fra stedsfestingen i GPS-dataene. I tillegg kan små SP-eksperimenter inkluderes i bakgrunnsunder-søkelsen for kryssvalidering og for estimering av enhetsverdier som kan være vanskelig å estimere basert på RP-data.
2) **Nasjonal RVU eller – fortrinnsvis – en skreddersydd reiseundersøkelse i felles estimering med RTM-modellen**. Sammenlignet med forslag (1.), legger denne tilnærmingen mindre vekt på presise data og legger vekt på konsistens og synergier med transportmodeller. Enhetsverdiene vil bli utledet fra nyttefunksjoner til transportmidlene i mode/destinasjons-valgmodellen som er en del av RTM-systemet. Kalibrering av rutevalg-modeller i nettverksmodellen (f.eks. CUBE) mot aggregerte datakilder kan i tillegg støtte estimering/anbefaling av enhetsverdier. Det anbefales sterkt at romlig informasjon fra reiseundersøkelsesdataene gis gjennom-gående med 8-sifrede grunnkretskoder (dvs. man bør gå bort fra gjeld-ende praksis med å gi grunnkretser med mindre enn 100 innbyggere 6-sifrede koder). Med det vil presisjonsnivået fortsatt være langt lavere enn ved GPS-sporing, men det bør være akseptabelt innenfor denne tilnærmingen.
3) En tredje tilnærming ville være å **beholde SP-metoden**. I dette tilfellet vil vi anbefale å bruke **flere godt utformede RP-casestudier for å validere/ justere det overordnede nivået av VTTS**. Kombinerte RP-SP-modeller vil bli anbefalt for å utnytte fordelene med begge datatyper. I den forbind-else vil det være å foretrekke å rekruttere deler av SP-utvalget fra områd-ene hvor RP-casestudiene gjennomføres.

1 Introduction

1.1 Background

All major national and international Value of time studies between 2000 and 2020 have been conducted with stated preference (SP) as the main method (Flügel and Halse (2021). The arguments of using SP data in the latest 2018-2019 Norwegian Valuation Study were 1) consistency with the previous 2009-2010 valuation study 2) avoiding risk of not being able to derive all unit values consistently with revealed preference data 3) econometric challenges with many RP data types such as high correlation and/or low variability of central attributes.

While stated preference (SP) studies build on an analysis of hypothetical choices in experimental settings without real-world consequences to the respondents, revealed preference (RP)-choices are observed in real-world settings and therefore the preferred method for deriving preferences. However, with RP data the researcher has little control over the data and little variation and/or high correlation in is a persistent challenge in RP-based estimation of unit values. This challenge can partly be overcome with larger data volume, which is more and more available due to the raise of Big data.

Note also that there is a long tradition – going back to McFadden, Talvitie and Associates (1977) – of estimating utility functions (and underlying valuation factors) in transport models based on travel survey data.

The transport authorities have intensified their work with Big Data and continuous travel surveys are being carried out in the largest cities. Furthermore, toll roads produce considerable amounts of relevant data that can potentially be exploited. The transport authorities are therefore interested in an assessment of whether it is possible to update current unit values with available Big data and RP data.

This report documents our assessment.

TØI and the transport authorities had several meetings where the selection of data sources and parts of the assessment where discussed. Notwithstanding, the assessment reflects the authors own evaluation and not necessary that of the clients.

1.2 Thematic introduction and motivation

In this report, we discuss several RP data sources, including Big Data, to estimate traveller's valuation of trip attributes.

In contrast to SP, RP data are based on real-world choices that implied real consequences for the decision makers. RP choices typically involve a process, which include time- and budget constraints and real-world constraints regarding the available choice set. This is illustrated in Figure 1.1 which is taken from a paper (McFadden 2001) based on McFadden's Nobel lecture from year 2000.

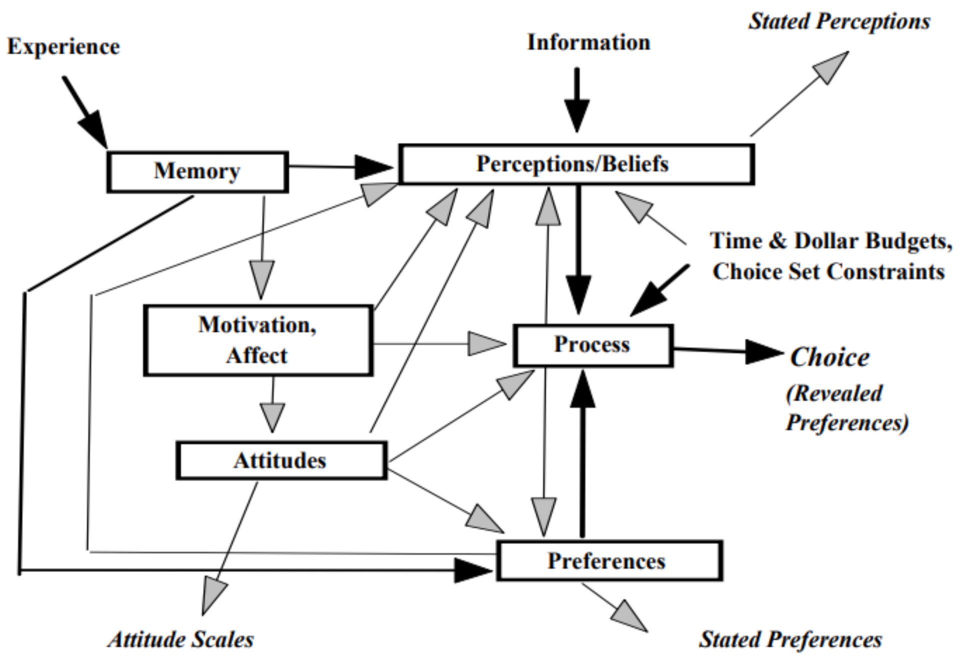


Figure 1.1: Choice process (source Mc Fadden 2001).

Big Data is a group of data characterised by large volume, and typically high velocity (high updating frequency). Many Big Data sources also come unstructured, e.g. in form of pictures, text or video. One may define Big Data as data types for which classical inference methods are not applicable. Machine learning is the predominant form of making inference from Big Data sources.

In the transport domain, literally all Big Data is RP data. Data from transport-related large-scale online computer games may be an example of Big Data of the stated preference type. However, computer games do typically not intend to emulate the (rather boring) reality of driving and are therefore of little help in deriving travel preferences.

A recent paper by Fayyaz et al. (2021) uses a driving simulator to measure the value of travel time savings (VTTS) and value of travel time reliability (VOR). To increase the realism, participants of the simulator-study are required to experience the travel time of their chosen route and actually pay any toll costs associated with the choice of a toll road. As this may increase the realism, and partly internalise time and budget constraints of the respondents, this so-called "economic driving simulator" would still be classified as SP data. An important real-world aspect of transport, and a determinant of specific preference, are the activities that are performed at the destination of the transport. Those are obviously not realistically given in the simulator. Another aspect is the comfort level which may differ between the simulator and real-world driving. The authors seem to agree with this interpretation and include "economic driving simulators" in the SP class of data (Figure 1.2).

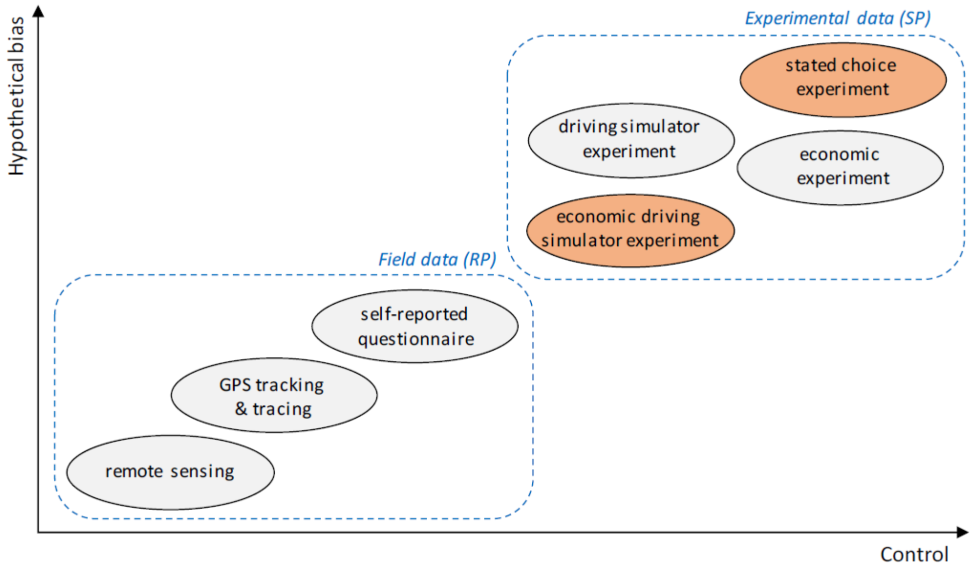


Figure 1.2: Some RP and SP data types (Source: Fayyaz et al 2021).

Figure 1.2 also illustrates the main trade-off between RP and SP data, i.e. the trade-off between hypothetical bias and the researchers control over the choice context. The latter facilitates sound econometric models and is the main reason for why SP approaches have been so popular.

Reducing the hypothetical bias is the main motivation to try to use RP data for deriving travelers preferences and willingness-to-pay. RP data types that are based on passive recruitment (like "remote sensing" in Figure 2) also avoid sample selection biases prone in SP surveys (Halse et al 2022). In addition, RP data in form of Big Data is collected continuously and without additional costs. There are therefore also practical advantages over SP studies that are conducted every 8-10 years (in the form of national valuation studies) and are quite expensive. Another criticism of SP studies are SP artifacts and effects that make SP results sensible to choices in the experimental design.

For the reasons mentioned above, the use of RP data for valuation is a topic that is of great interest among transport economics and practitioners, both nationally and internationally.

In a large meta-analysis on time values (Wardman, Chintakayala and de Jong 2016) the proportion of studies using RP data is 18%, with a declining trend between 1990 and 2011, the period in which SP data increased significantly in popularity. However, there are many indications that RP data is making a strong comeback due to access to Big Data and new analysis possibilities such as machine learning.

Norway is arguably a good area to utilize RP data for valuation as road tolls are very common. Road tolls allow us to observe trade-offs between travel time and travel costs of car drives. These trade-off are essential in estimated the value of travel time savings (VTTS).

The following figure summarises the main motivations for using RP and Big Data for valuation in Norway and in general. Advantages that are general to RP data types are given in the blue boxes. Advantages specific to Big Data (compared to more traditional RP) are given in green boxes.

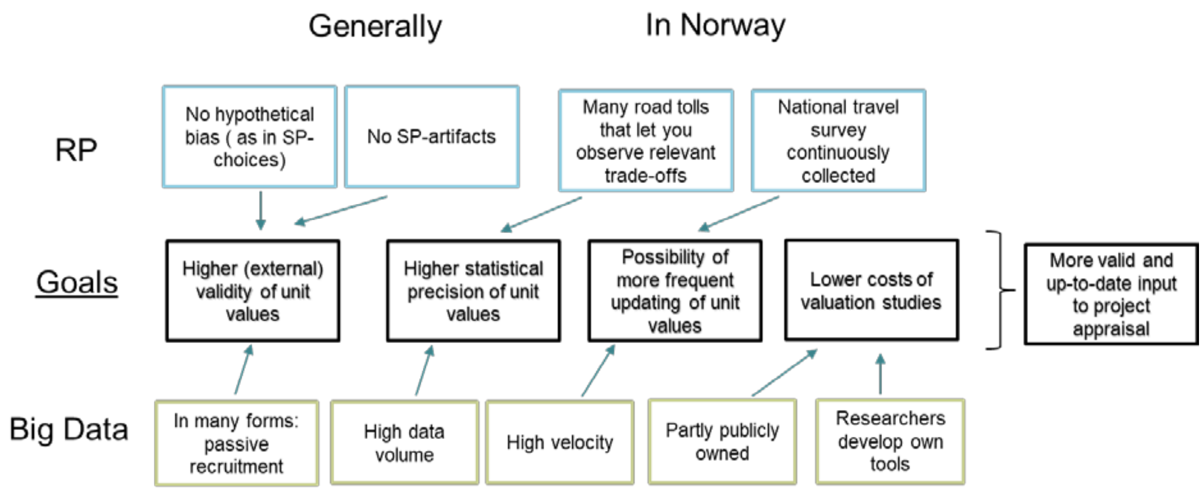


Figure 1.3: Overview over motivation of use of revealed preference (RP) data and Big Data for transport valuation

This report is intended to give an overview of relevant data sources (RP/Big Data) and assess the prospects of such data types in the Norwegian case, i.e. for the particular unit values from the latest Norwegian Valuation Study (Flügel et al. (2020b)).

We are not aware of similar overview/assessment reports. We therefore believe that this report can be of interest to an international audience. Many discussions about types of data and unit values should transfer to other counties. That said, the discussion regarding access, experience and synergies to (Norwegian) transport models is specific to the Norwegian case.

2 Initial work and selection

2.1 Selected unit values from Valuation study

Table 2.1 reports on the list of unit values that are included in this study.

Table 2.1: Unit values included in initial selection.

Unit value	Unit	Segmentation	Table in Norwegian valuation report (Flügel et al. 2020b)
In-vehicle time car driver (VTTS)	NOK/hour	Distance group, Purpose	E1
In-vehicle time car passenger	NOK/hour	Distance group, Purpose	E1
In-vehicle time buss	NOK/hour	Distance group, Purpose	E3
In-vehicle time train	NOK/hour	Distance group, Purpose	E3
In-vehicle time metro/tram	NOK/hour	Purpose	E3
In-vehicle time Boat	NOK/hour	Distance group, Purpose	E3
In-vehicle time Air	NOK/hour	Purpose	E3
In-vehicle time ferry	NOK/hour	Purpose	E2
Time cycling	NOK/hour	Purpose, Infrastructure type	E4
Time walking	NOK/hour	Purpose, Infrastructure type	E5
Headway (PT)	Factor	None**	E6
Transfer time (PT)	Factor	Purpose, Infrastructure type, own values for air	E7/E13
Transfer penalty (PT)	Minutes*	None	E7
Access time (PT)	Factor	None (exception Air: access mode)	E8 and E15
Time Variability	Factor***	None	E9
Delays	Factor	None	E10
Road congestion	Factor	Driver vs passenger, Purpose, degree of congestion (free flow, moderate, severe)	E11
In-vehicle crowding (PT)	Factor	Trip purpose, Sitting vs standing passenger	E12
Cancellation for Air	Hours*	None	E14
Future car technology	Factor	By degree of automation (partial, high, full-private, full-shared)	7.9
Mobil coverage (PT)	Factor	By degree of coverage (god, medium, bad/none)	5.23
Insecurity of avalanches	Various		Se report by (Navrud, Magnussen and Veisten 2020)

* is essentially a factor on the VTTS as well **factor depends non-linearly on the size of headway in reference situation, *** applied to one standard deviation of travel time

We can distinguish between unit values that are reported as monetary values per hour (NOK/hour) and those unit values that are reported as factors, also called VTTS multipliers. The former applies to VTTS for in-vehicle time on all main travel modes. It requires a measure or estimate of the marginal utility of income, which is typically assumed identical to the absolute value of the parameter related to the cost-attribute of travel alternatives. The latter (factors on the VTTS) applies to most of the other unit values. In these cases, it may not be necessary to know the cost parameter. Under the assumption that the cost parameter is not context specific, VTTS multiplies can simply be derived as ratios of the parameter of the underlying time component (access time, time in congestion etc) and the parameter for in-vehicle time.

Note that Transfer penalty and Penalty for cancellation are reported in full minutes/hours. However, they function essentially like multipliers, as simply dividing by 60 minutes would give the corresponding VTTS multiplier.

VTTS factors for in-vehicle crowding are given as a function of the level of congestion, first in terms of occupied sitting places and then (after all sitting places are occupied) in terms of standing passengers per square meter. There are also two sets of functions, one for sitting passengers and one for standing passengers. Note that these so-called crowding functions are given relative to the VTTS in uncrowded vehicles. The minimum value of these functions is therefore 1. In order to apply this, one has to estimate a VTTS in absolute terms for uncrowded vehicles. Note that this does not equal the unit value of the VTTS which implicitly applies to a vehicle with "average" crowding level.

The Value of Reliability demands the quantification of a standard-deviation (or variance) of travel time for different alternatives. Note that this information is not given in Level-of-service (LoS) data of the RTM-transport model (Rekdal et al. 2021).

2.2 Initial comments on choice context and analysing possibilities

In the 2018-2019 valuation study (Flügel et al. 2020b), all unit values where estimated from route choice settings with the only exception of walk and cycle which also included mode choice in the choice experiments.

Route choice is the preferred type of choice context for measuring preference for a given user-group. The main reason being that trade-offs between two attributes (say time and cost) is to a larger degree controlled for other influences. This applies in particular when the comfort and safety level of competing routes are similar such that routes can be treated as 'non-labelled'. In a mode choice setting, we have labelled alternatives (car, bus, trains etc) and the observed choice may be influenced by other factors. The average effects of these other measures can be captured by alternative specific constants (ASCs). However ASCs might be correlated with the preferences for given attributes. In this case the inclusion of ASCs may not fully suffice and there is a danger of confounding effects that may influence the estimation of valuation parameters.[1]

Another aspect of mode choice modelling is that the value of the attributes, for example travel time and travel cost, often depends of the underlying route choice within each transport mode. In travel survey data, the mode choice is typically asked for, but the route choice is not reported. To infer attribute values for modelling based on travel survey data one needs either to ask the respondents to report such values directly or one needs to extract this information from other sources, e.g. as Level-of-service data from transport

[1] As discussed in section 3.4.1 and shown empirically in section 5.3, the challenge of isolating the ASC and other effects can be a challenge also in route choice analysis with highly aggregated data.

models. Neither option is optimal. Self-reporting is often unreliable and not available for non-chosen alternatives. Inferring attribute values from transport models is the more "objective" alternative, but it relies on that the transport models have a realistic modelling of route choice, which may not always be the case.

When inferring parameters from RP-based route choice, there is a challenge regarding the VTTS of car passenger, as it is only the route choice of the driver that can be observed. An interesting alternative is to study RP choices in apps for ride-haling (Buchholz et al. 2020, Goldszmidt et al. 2020). However, in current studies the VTTS applies only to waiting times, not in-vehicle time (see section 2.4).

Destination choice modelling is applied in Zhu and Ye (2018). It seems however hard to control for unobserved factors (particularities – including the knowledge – of the different destinations) such to be able to robustly estimate VTTS in this choice context alone.[2]

Another challenge with RP data is that real-world choices can only be observed with current technology. This makes it impossible to study to study preference for future car technology (as done in the SP case by Flügel et al. (2019a)). To a lesser degree this also applies to Mobile coverage in public transport, which can only be measured with RP data to the level of current mobile coverage. Future mobile coverage (perfect coverage without disconnects) and high speed (5G) are currently not widely observed.

The preferred method of deriving preferences and valuation is by studying *individual* choice and analysing this data in the setup of discrete choice models. In this setup, the researcher has to define the

a) the decision makers
b) the choice set, i.e. a set of alternatives that are discrete, exhaustive, mutually exclusive and finite
c) characteristics (attributes) of different alternatives
d) a decision rule.

The information for a-d) may come from different data sources. Often we observed choices with one type of dataset (e.g. RVU) but need to use additional data sets (e.g. LoS matrices from network models) to measure characteristics of alternatives. This is because the dataset that provides the choices does often only include the characteristics of the chosen mode.

Note that the assignment of choice sets typically involves some kind of modelling or heuristics from the researcher. Sociodemographic data and background data on individuals (as owning a drivers licence) may be important information in modelling the availability of travel modes.

In a route choice setting in non-trivial networks, an additional challenge is that the set of possible routes is very large. In these settings, choice set generation is an important element in the modelling approach.

[2] Combining travel mode choice and destination choice is likely an improvement. In these set ups the VTTS is likely to be more reliably inferred from parameters related to mode choice (compared to destination choice). E.g. in the RTM estimation, VTTS is (indirectly) included in utility function for modes, rather than the size-function for destination choice. This is described in detail in section 4.1.

In order to be able to identify valuation parameters in a discrete choice setup, the data needs to include choices of different alternatives. When all decision makers make the same choice, we can't estimate parameters. Estimation parameters may also be hard to estimate if the correlation among central attributes is very strong and/or if there is little variation in attributes.

In lack of individual data, one can also try to infer preferences and valuation from aggregated data. This is typically only possible when aggregated data reflect some form of market shares. For instance, traffic count data may be used to infer market shares between two parallel motorways allowing to study preference based on the implied route choice and characteristics (Tveter et al. 2020). In most cases the information will be rather coarse such that trade-offs are hard to observe with the required level of detailed.

While aggregated data does typically contain limited information about choices taken by travelers, it is possible to use this data to calibrate function in transport models and derive updated valuation data from this. For instance, it has been observed that the SP-estimated VTTS unit values do a bad job getting route choice in the RTM/Cube-system to match traffic counts. By increasing the VTTS one could obtain a better fit (Steinsland 2022). Provided that the route choice functions in RTM are correctly specified elsewhere, this may point to that the 'real' (RP) VTTS is higher than estimate in SP. Calibration against aggregated traffic counts works also for disaggregated (agent-based) transport simulation models (Flötteröd, Bierlaire and Nagel 2011).

Preference may also be derived from macroeconomic variables and/or theoretical models. E.g. the Value of time for leisure may be approximated by the wage rate. However empirical results show that such theoretical derivations are often not directly supported by data.

Meta-analysis is another method that is sometimes applied, but is not further discussed in this report.

Table 2.2 summarises some of our initial thoughts regarding choice contexts and types of RP data. RP data types are introduced in more detail in section 2.5.

Table 2.2: Initial assessment of choice context information in types of RP data sources.

Data type	Info on mode choice	Info on route choice	Info on departure /waiting time choice	Background information
Disaggregate survey data	Rich	Limited	Limited	Rich
Disaggregated GPS-tracking	Limited/ Potentially rich	Rich	Potentially rich	May require additional surveys
Disaggregated choice data (e.g. from apps)	Limited/ Potentially rich	Limited	Potentially Rich	May require additional surveys
Aggregated data (e.g. count data)	Limited	Limited	Limited	No

2.3 Work task overview

The project work is structured in different tasks as illustrated in Figure 2.1.

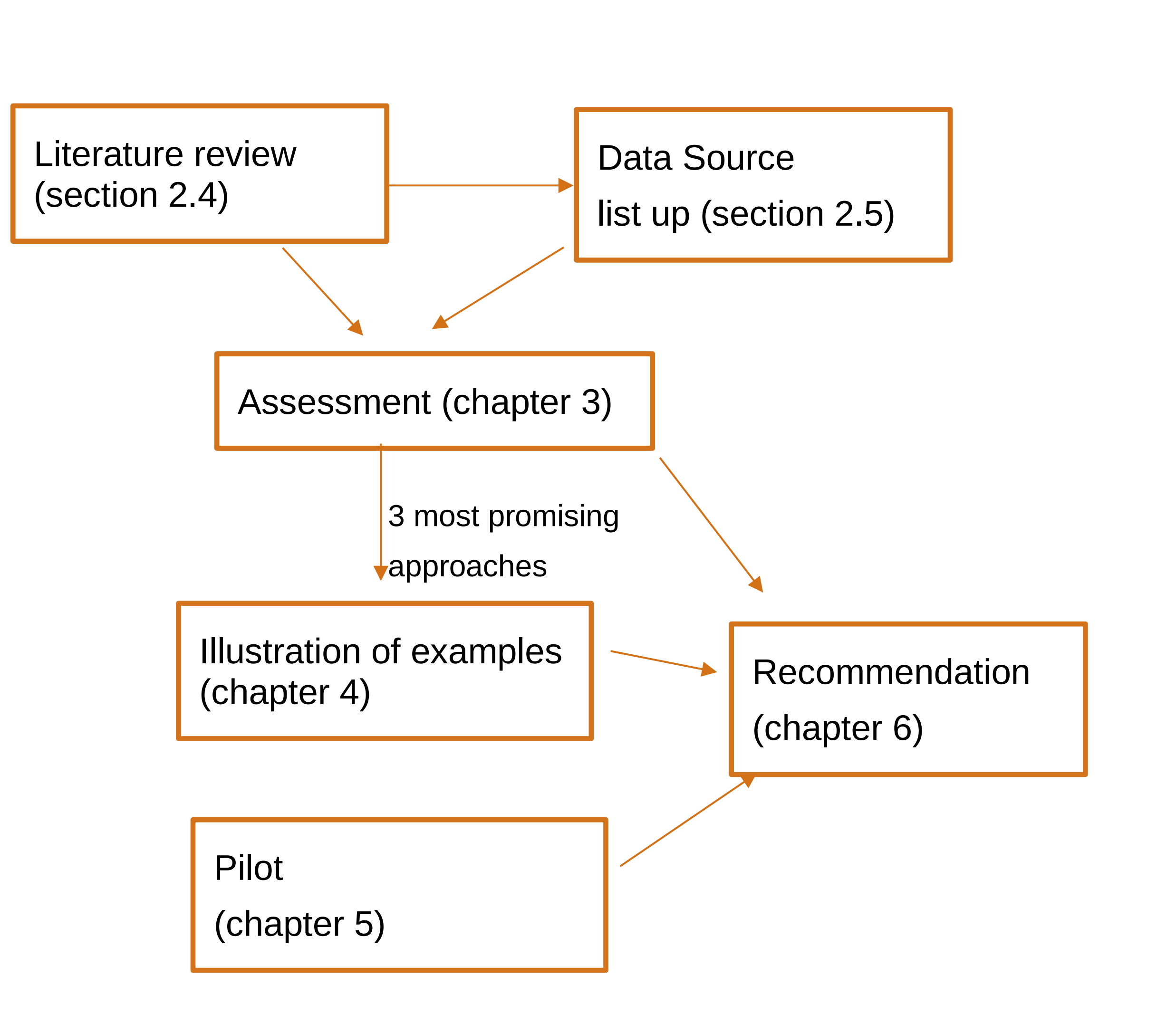


Figure 2.1: Work steps of project

As part of the initial work, prior to the assessment, a literature review of relevant national and international studies is given in section 2.4.

Based on the literature, review, the author's own experience and input from the clients, we then give a list up and a short description of relevant data types (section 2.5).

The assessment of relevant combination of data types and unit values are given in chapter 3.

The three most promising approaches as assessment in chapter 3, are then illustrated from a more practical point of view in chapter 4.

Chapter 5 is a short case study ("pilot") on data from Telia, TomTom and traffic counts, illustrating some of the challenges of aggregated data.

Our work is summed up and discussed in a recommendation chapter (chapter 6).

2.4 Literature review

One can classify studies found in the literature by the unit value, mode group (car, PT or walk/cycle) and RP data type. Table 2.3 gives a brief overview of some highly relevant studies.

Table 2.3: Overview over central literature.

Unit value	Mode	RP data type with most relevant reference
VTTS (invehicle)	Car (driver, passenger)	Mobile data (Bwambale, Choudhury and Hess 2019) Specific route choice survey (Fezzi, Bateman and Ferrini 2014) Toll transaction data (Cetin et al. 2021) Traffic count data (Tveter et al. 2020) Travel Survey data (Varela, Börjesson and Daly 2018) Floating car data and automatic number plate recognition (ANPR) cameras (Dabbas, Fourati and Friedrich 2021)* GPS-tracking (Montini, Antoniou and Axhausen 2017)*
VTTS (waiting)	Taxi	Ride-hail platform (Buchholz et al. 2020)
VTTS (various time components)	Public transport	Mode choice survey (Flügel et al. 2015) Travel Survey data (Rekdal et al. 2021) GPS-data (Chepuri et al. 2020) Smart card (Jánošíková, Slavík and Koháni 2014)
VTTS	Cycling	GPS-data from App (Flügel et al. 2019b)
Crowding	Public transport	Survey (Batarce, Muñoz and Ortúzar 2016) Observation on stations (Kroes et al. 2014) Smart card (Hörcher, Graham and Anderson 2017)
Value of reliability	Car (driver, passenger)	GPS data (Carrion and Levinson 2013) Transaction data (Bento et al 2020)

* Include a route choice model but does not estimate VTTS (the route choice model has no cost-attribute).

The Value of Travel Time Savings (VTTS) for road transport is most widely studied unit value with RP data. The typical choice context is route choice, i.e. the choice between two alternative options within the same mode of transport. The literature review showed that route choice can be observed with or derived from by different data types, including mobile data (Bwambale et al. 2019) and toll transaction data (Carrion and Levinson 2013)[3]. In case studies, one can also use aggregated traffic count data (Tveter et al. 2020) or specific route choice surveys (Fezzi et al. 2014). More generally, travel surveys can also be used to estimate VTTS, but here mode choice is the typical choice context (Varela et al. 2018).

An interesting approach is the use of Mobility-as-a-service (MaaS) app data. For instance does Buchholz et al. (2020) use app data from Liftago in Prague to derive the value of waiting time for taxi services. The choice the users of that app are facing is illustrated in Figure 2.2 (left panel).

[3] US studies based on toll transaction data, as Carrion, C. & D. Levinson (2013), typically consider cases where drivers pay a toll to access a lane which is otherwise only available for high-occupancy vehicles. Such lanes are referred to as high-occupancy toll (HOT) lanes. In Norway, such lanes do not exist.

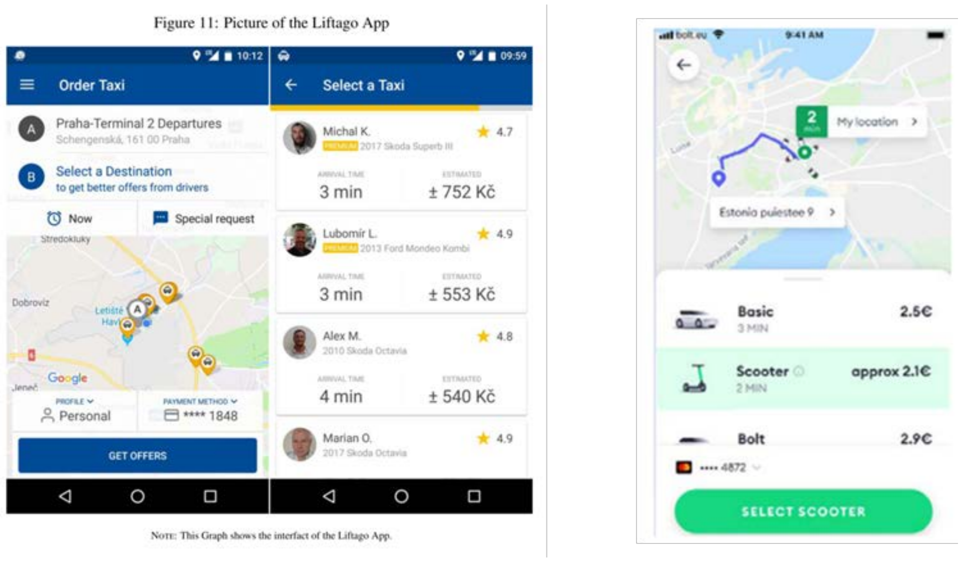


Figure 2.2 Examples of app-data (left panel: source: Buchholz et al. (2020); right panel Johansen (2022).

Goldszmidt et al. (2020) used a similar App (Lyft) in the US. They introduced price different by means of controlled experiments (offer “hidden” price discounts for a random treatment group of App-users).

Recently, a TØI-report (Johansen 2022) used app-data from Bolt to model mode choice between rail-hailing and e-scooter in Oslo and 9 other European cities. The choice context is illustrated in in the right panel of Figure 2.2.

An interesting study from a data perspective is Dabbas et al. (2021) who use floating car data and automatic number plate recognition (ANPR) cameras to study car route choice in the city of Duisburg, Germany. The floating car data consists of a mix of data sources including “fleet management platforms, taxi-tracking data, and navigation devices”. The data comes from a commercial provider and is unfortunately not described in much detail in the paper. For valuation, the study used detector data and automatic number plate recognition (ANPR) cameras. The latter is installed specifically for the study as Figure 2.3 illustrates.

Figure 2.3: Illustration of the use of automatic number plate recognition cameras (Source: Dabbas et al 2021)

Zannat and Choudhury (2019) give a comprehensive literature overview over Big Data in public transport. As shown in there overview (see appendix A) a huge majority of studies are based on Smart Card data (SCD). It can be argued that SCD is an outdated technology, at least in Norway, and the trend is going into mobile apps. We have there not focused on this branch of literature. However, some studies on smart card data, i.e. the ones concerning route choice modelling (see appendix A) are still relevant given that app-tracking data can provide same (and even more detailed) information on routes.[4]

Preference for crowding have been derived from different RP data sources as surveys (Batarce et al. 2016) and smart cards (Hörcher et al. 2017). In a more limited case, Kroes et al. (2014) also used observation at stations in Paris to investigate trade-offs between crowding and waiting times.

Besides the mentioned study by Tveter et al. (2020), there are more Norwegian studies worth mentioning.

Flügel et al. (2015) uses survey data to model mode choice in the long-distance corridors in Norway. Both RP and SP data (including an hypothetical High-Speed-Rail option) where collected and analysed in a combined estimation model.

RVU data from 2013/2014 was used for the estimation of the current RTM-model system (Rekdal et al. 2021). This is discussed further in section 4.1.

RVU data for 2018/2019 (combined with data from Ruter-MIS) was used for the estimation of PriSimOV model for Ruter. The model uses a similar method as in the MPM23 models (Flügel et al 2015). Note, that the in the second version of the MPM23 model (Flügel et al 2017) the model was specified in two variants, one variant where the VTTS was estimated from the RP data and one variant where the VTTS was fixed to values from the SP values from the 2009/2010 Norwegian valuation study.

The National Public Roads Administration (NPRA) tendered a pilot study to assess whether mobile data are suitable for measuring trips within and through the Lillehammer area.[5] Both major mobile network operators in Norway contributed to the study. NPRA concluded that movement data from the mobile network is well suitable to monitor movement patterns between greater geographic areas on a macroscopic level in near real-time. Furthermore, an estimation of travel time between[6] cities is considered possible. For calibration of transport models or estimating future travel patterns, however, mobile data is recognized to be unsuitable.

[4] For that GPS-coordinates need to be mapped to stations.

[5] We have gotten access to an internal report by NPRA.

[6] However, exact timestamp of start and end of a trip is unsure, since the phone first has to leave the cell and connect to a new one.

2.5 Relevant data sources

2.5.1 Overview of initially included data types

Table 2.4 gives an overview over data types that are initially evaluated in this project. The once that are deemed relevant as a primary data source for this project are further described in section 2.5.2 -2.5.11. To be included as primary data source the following four criteria needs all to be met:

1) The data needs to be available in Norway or there needs to be clear path to how it can be made available.
2) The data set must give direct or indirect information on travellers behaviour, either in form of individual choices or in form of aggregated market shares.
3) The data set needs to enable the attachment of relevant and sufficiently precise attributes to the different alternatives in the choice set.
4) Some of the choices that are observed need to imply an actual trade-off between at least two attributes that are relevant for the underlying unit value. Attributes, like time and cost, can be overall positively correlated (and they often are in practice), but there needs to be same mechanisms (at least for a subset of choices) where variation in the data is invoked (e.g. through road tolls).

Note that 4) is specific to valuation and would not apply in that form for deriving elasticities of demand. For elasticities, one needs to observe changes in demand given changes in one attribute. While there exists studies of cross-sectional elasticities, one is typically interested in elasticities over time. The time-aspect is not explicit in most valuation studies, although variation in trade-offs can also come from different observations over time. In a valuation study, the focus is on analysing how (different) persons choose in different situations, i.e. under different choice sets. We therefore do not have a particular focus on time series and historical data sets. Observing the actual choice, the underlying choice set and (varying) attributes of all relevant alternatives, is the most central aspect for the selection of data sources.

Table 2.4: Overview of data sources

Considered data source	Possible to derive choices and preferences	Only secondary data source (to quantify attributes or for further calibration of transport models).	Assessed as not relevant for this project
RVU (national)	X		
Movement data from mobile network	X		
App data panel	X		
Movement data (app) from commercial enterprises	X		
Automatic traffic counters	X		
Toll transaction data	X		
Reisetider.no		X	
Automated passenger counts	(X)	X	
MaaS ordering data	X		
Camera-based crowd counts at stations	X		
Automatic number plate recognition (ANPR) cameras	Combined as "dedicated		

Considered data source	Possible to derive choices and preferences	Only secondary data source (to quantify attributes or for further calibration of transport models).	Assessed as not relevant for this project
Various sensor data (RFID signal, Bluetooth, magnetic signature)	cameras and sensors”		
Real time timetables for public transport		X	
Weather forecasts		(X)	X
Fleet data			X
Social media data			X
RP data from Valuation study			X
Smart card data			X
PT ticket sale statistics			X
Ruter-MIS			X

As indicated in Table 2.4, we excluded some data sources from the assessment. The following is an justification for that.

Weather forecasts is a Big Data source that is sometimes used as an explanatory variables in the modelling of trip frequency, departure time choice, transport mode choice and route choice. This seems particular meaningful in choice context that involve cycling or walking.[7]

With “Fleet data” we mean positioning data from individual vehicles in a fleet.[8] Fleet data can be segmented into private vehicles, commercial (heavy duty) vehicles and taxis. For private vehicles, data in general is not available. Modern vehicles send a lot of information to the manufacturer, but these data are not publicly available. To our knowledge all new cars have to be equipped with a “black box” from July 2022, however only the last few seconds of vehicle data will be stored and made accessible in case of an accident. No location data is stored. For commercial vehicles, fleet data is often available to the operating (logistics) company. Usually, these data are not available outside the companies. Taxi fleet data is not included as there are no unit values specific for taxi in Norwegian handbook and it is not obvious how these data can be utilized for other valuations.

Reisetider.no is a service hosted by the NPRA on selected roads in Norway. Road side stations measure the RFID signal from the toll device (“bombrikke”). The system measures the time between passages of individual vehicles between the roadside stations. The travel

[7] As the weather does typically not directly influence the travel cost and travel time components, it is rather a mean to control for otherwise unobserved factors (i.e. the weather) and will in most cases not of crucial importance for the derivation of unit values in our shortlist in section 2.1. Unit values should apply to “average” weather conditions (across the whole nation and a whole year). Controlling for weather becomes an issue when data collection is concentrated on specific periods such that an “average” weather cannot be expected, e.g. due to seasonal effects. This – by the way – is an somewhat neglected issue in most SP studies.

[8] Positioning data generated by GNSS devices in vehicles is stored by fleet owners, aggregates can be available. Typically, these data are produced for logistics purposes and fleet information (distribution- and taxi companies). In modern (connected) vehicles positioning data and some kinds of vehicle information (OBD (On Board Diagnostic) data: e.g. energy uptake, speed, engine temperatures…) are transmitted to the OEM (Original Equipment Manufacturer). Truck companies like Scania and Volvo build their fleet monitors on these kinds of data. For a future regulation, these data could be made available for research on an aggregated level (e.g. k-anonymity).

times are aggregated and shown on a map in real time. The system can give information about the congestion situation on selected roads. However, due to built-in privacy measures ("privacy by design"), individual data is not accessible.

Social media data is an important Big Data source but the application in the transport valuation seems rather limited. Low spatial granularity is a major limitation.

RP data from the Valuation data would have been a very nice data source at it would facilitate RP-SP estimation models for a consistent sample across SP and RP. However, the spatial information reported in the survey is unfortunately too coarse for many observations[9] to derive Level-of-service information from network models. This typically require, at least, information on a level of basic statistical unit (BSU, "grunnkrets").

Smart card data is – as mentioned in the previous section – a popular data source to study behavior for public transport services. This is especially true in PT-systems where activating the smart card is mandatory before boarding each PT vehicle. This is not the case in Norwegian cities and smart cards are widely replaced by mobile apps.

PT ticket sale statistics can be provided by PT operators such as Ruter AS in the Oslo area. For short distance PT in city areas, the data is likely not able to provide sufficient geographical information. For instance, how many tickets are sold within "zone 1" in Oslo cannot be used to study trade-offs, even if we could subdivide sales in submodes (bus, metro, light train), because one would need more detailed information on the origin-destination (OD) in order to assign attributes (travel time).[10] Sales statistics for long distance traffic is more relevant, as one typically has better information on the OD. To derive market shares for different long-distance transport modes, one would combine information from several companies (including private airlines) which might not be possible.

Ruter-MIS consists of several data collections, most notably a travel survey that is continuously collected on work-days. The survey has a lot of similarities to the national RVU but has a spatially limited to the Oslo-metropolitan area and with that less relevant for estimation of *national* unit values.

The rest of the section gives a short descriptions of the data types included in assessment. The description focuses on the technology. The properties and capabilities of these data types for valuation is discussed in chapter 3.4.1 and consecutive sections.

2.5.2 National RVU

The national travel survey data (RVU) is a traditional travel survey that has been conducted since 1985. From 2016 onwards, the data collection is continuous.

In RVU 2016-2019, the sample of RVU is deducted from the central population register and executed as a self-administered web survey (an invitation letter is send out in advance). Telephone interviews are used to follow up on those who did not answer online. From 2.

[9] Precise geographical information was obtained for respondents that used a google maps solution. Due to privacy concerns this precise data was decoupled from the survey data and is not longer available in the same data set as the background variables of respondents.

[10] Future version of the Ruter-app may provide more detailed information, and might in that case be fallen under the category "MaaS ordering data".

quarter 2020, RVU was only conducted as a telephone interview, (without an invitation letter in advance) The sample was based on a representative sample from Data Factory's database for market and opinion polling (Opinion 2021).

Figure 2.4 shows that the response rate in recent years has been much lower than it used to be. On the other side, the total number of observations has increased due to a strong increase in the use of regional "supplementary" samples. In RVU 2020, the total sample size of 38,500 interviews (with 32,000 interviews from regional municipalities with supplementary samples).

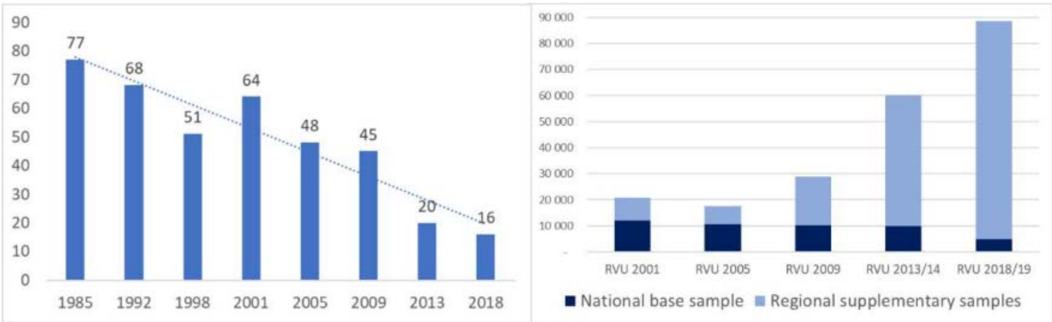


Figure S.1: Developments over the years of national travel surveying in Norway. Diagram to the left: Response rates 1985-2018. Diagram to the right: Sample sizes (number of interviews) and geographical coverage 2001-2018/19.

Figure 2.4: Historic response rate and sample size in RVU (Source: Grue, Landa-Mata and Flotve (2021))

The core of RVU are travel diaries reporting when, by what, where and why (trip purpose) travel occurs. Besides the travel diary, the survey includes several background variables.

2.5.3 Movement data from mobile network

CDR (Call Detail Record) data are commonly analysed for transportation research. The data are recorded for billing purposes and contain information (among others) about the handset (e.g. mobile phone), timestamp, type of connection (voice, data) and cell ID (cell tower). These data are not continuous in nature, they are generated when the handset contacts the mobile network. Under heavy usage (active data connection, frequent phone calls), the data density can be high. Less frequent usage (phone in storage during a trip) will lead to gaps (up to several hours) in the route, with the handset jumping over longer distances.

These data can with little effort (e.g. correction for market shares, aggregation) be used to analyse population density in interest areas and to generate OD-flows. In order to analyse route choice, additional steps must be taken. An approach suggested by Bwambale et al. (Bwambale et al. 2019).

Handover data might deliver more accurate positioning, however these data usually require a dedicated setup in the network, since they are not stored permanently as a standard. The handover regulates the traffic in the mobile network, e.g. handsets signing out of the broadcast area of one cell tower and signing in to the next one. Especially in urban areas, broadcast areas overlap and a handset in a fixed position might connect to different cell towers over time, generating artifact hops. Therefore, these data are to be treated with care.

Usually, data are aggregated with respect to k-anonymity criteria, e.g. data from at least 15 handsets are aggregated before the data can be accessed.

2.5.4 App data panel

Here, when we mention app data from a dedicated panel, we mean dedicated smartphone applications that record location and timestamp. The panel is recruited for the study purpose. The location data is deducted from GPS (Global Positioning System), enriched with A-GPS (assisted GPS) techniques (e.g. wireless network maps provided from online databases). The researcher has access to data from single individuals.

With a high density of data points, route choice can easily be deducted. While it is possible to distinguish between parallel streets in urban areas, the chosen side of the road cannot be determined, due to the error margin in the location data. Typical resolution varies between 5 and 15 m. Further developments in GNSS (Global Navigation Satellite System) technology applying multifrequency positioning will bring this error margin down to cm levels. The first smartphones supporting this technology have reached the market (e.g. Google Pixel, Samsung Galaxy S20 phones).

With more sophisticated apps, the mode choice can be measured. By analyzing data from additional sensors in the smartphone (mainly accelerometer, magnetometer), typical movement patterns can be analysed, and the transport mode can be derived. Examples of these kinds of tracking apps are sense.dat (mobidot) and Fotefar (Fotefar AS) (see also section 4.2).

Additional surveys, either given directly in the app or in separate schemes can give background information.

2.5.5 Movement data (app data) from commercial enterprises

Location data can also be purchased from commercial enterprises. Typical cases are crowd-sourced data that are generated by (recreational) athletes and recorded by e.g. sports tracker apps like Endomondo or Strava and tracking devices from Garmin, Fitbit or Polar. These data typically cover exercise and recreational trips, in some cases commuting trips. Navigation devices (TomTom) in cars record positioning data that can be available.

The data are originating from the same sensors as in the App (panel) data mentioned above. Usually, data access is restricted to aggregates only (see mobile network data) and little background (sociographic) information is available.

2.5.6 Automatic traffic counters (ATC)

Many major roads in Norway have automatic traffic counters (ATC) installed. The most common method are induction coils that are installed in the asphalt layer of the street. A moving mass of conducting material (metal) will generate an electrical induction pulse in the coil. With two coils separated in a known distance, the speed of the vehicle can be measured. From the shape of the pulse, the mass of the vehicle can be estimated. This allows to distinguish LDV and HDV. The technology works well for cars, trucks and bicycles. Downsides are high installation costs, vulnerability against mechanical damage (construction works) and a required minimum speed. The latter makes the technology inapt to measure high levels of congestion in a traffic system.

Newer developments in traffic counters include automated camera (see next section) counts and magnetic detectors. The latter are devices that can register the magnetic signature of a vehicle. This allows to identify make and model of the vehicle, in addition to the conventional parameters (timestamp and speed).

2.5.7 Automatic number plate recognition (ANPR) cameras and sensor data that allow to track persons or vehicles

Camera feeds can be evaluated with the help of machine learning algorithms (MLA) in order to produce automated camera counts. In addition to count and speed, the registration number can be read by the algorithm (special case: toll transaction data, see below). This allows to identify the passing frequency for a vehicle and to follow the vehicle through the road network. Data from permanently installed roadside units can be made available for research (not available per 2021), although this might require k-anonymity. Reduced costs of high quality cameras allow to setup (mobile) sets of cameras for case studies.

Recent developments in MLA make it possible to count the passengers in cars with camera technology.[11] One could also image recognizing features of the cars such as ski-boxes or car-trailers.

To contrast it from ATC-data and toll transaction data (se next section), where cameras/sensors are permanently installed for other purposes, we assess this data type as "dedicated camera and sensors". This is further described section 3.4.1 and 3.4.8.

Sensors include RFID signal from road toll devices ("bombrikke") for which dedicated receivers can be installed, bluetooth tracking and magnetic sensors as employed by Disruptive engineering.[12] The latter is not meant to track vehicles and is therefore not further discussed here.

2.5.8 Toll transaction data

In Norway, road toll is collected electronically. The passage is registered in two ways: A camera reads the license plate number and a RFID-type (Radio Frequency IDentification) device ("bombrikke") transmits (encrypted) identification data between the vehicle and the toll station.

From these data, counts, timestamps and passing frequency can be deducted. These data can be made available for research (not available per 2021), although this might require k-anonymity.

2.5.9 Automated passenger counts (APC)

In metro, train and bus the current number of passengers is counted by camera technology, mobile phone tracking and/or light barriers.

[11] https://www.countinghero.com/ is a company that seems to offer such/similar services

[12] https://www.dengineering.no/#Sensor-System

With currently employed technology, one can only count embarking and disembarking persons, but cannot track a person through his/her entire public transport ride. This should be possible with cameras positioned in the vehicles and access to advanced MLA. Such tracking data would allow deriving OD-counts, which would help studying preferences and valuation. However, as it is currently unclear if such data can technically and legally be collected, we assess APC data without tracking in the assessment (section 3.6). That tracking of persons are technically possible (at least in a lab setting) is demonstrated by Velastin et al. (2020).

Figure 8. Illustrative tracking example. (**Left**) A simple case; (**Right**) a more complex case. The numbers and colors correspond to unique person identifiers, the trailing tails show their trajectories.

Figure 2.5: Illustration of camera tracking (Source: Velastin et al 2020)

2.5.10 Camera-based crowd counts

This works similar to APC but in public spaces such at platform. I.e. cameras are installed and record crowds e.g. public squares or streets, and machine learning algorithmics (MLAs) deliver the counts. A possible application can be to measure waiting time on public transport platforms. Identification of individuals will allow to measure individual preferences, e.g. how many people rather wait for the next train, if they see that the current one is crowded.

2.5.11 MaaS ordering data

Data from mobility companies like UBER, Lyft can give information on personal preferences as app users may be confronted with alternative options when booking a trip. E.g. when users can choose between cheaper trips with longer waiting time or more expensive trips with shorter waiting time.

Information must be stored as it appears on the screen of the ordering app (see Figure 5 above). Compared to app tracking data (section 2.5.4) geographical information on routes is not required (however it may facilitate interesting additional analysis once it is available).

Such data is not exclusively related to MaaS and could also stem from more traditional transport means. E.g. app data from train operators could possibly be used to study choices between train and bus or choices between flytoget and VY-trains

This data is of only relevance if users do actually order transport solutions (not just get the information) and when they were confronted with alternatives that differ in relevant characteristics.

3 Assessment

3.1 Included combinations of data sources and unit values

As described in the section above, we consider 10 types of RP/big data for valuation.

Table 3.1 documents combinations of data sources and unit values that are included in the assessment. Unit values are grouped in Table 3.1 to make the table easier to read. In some instances, we divided the assessment by different modes. In instances where the assessment would be very similar, we group unit values also in the assessment.

Combination that are marked red and orange are deemed nor promising ("not pr.") and not applicable ("not ap.").

Table 3.1: Combinations of data types and (groups of) unit values included in the assessment. Legend to table: B1-B4 relates to the block the combination is included in. W: walk, C:Cycle, PT: public transport, "short": short distance PT mode such as bus, metro, train, and passenger boat, "long": long distance PT mode such as like air and ferry, not pr: not promising, not ap. : not applicable

	VTTS car	VTTS W/C	VTTS PT (short distance modes)	VTTS PT (long distance modes)	Time components (PT)	Invehicle crowding	PT Delays / variablity	Car Time Variability	Road congestion	Insecurity of avalances
National RVU	**<u>B1</u>**	**B2**	**B2**	**B2**	**B2**	not pr.	not pr.	not pr.	**B2**	not pr.
mobile data	**<u>B1</u>**	not pr.	not pr.	B3	not pr.	not pr.	not pr.	not pr.	not pr.	not pr.
App panel with GPS-tracking	**<u>B1</u>**	B4	**B3**	**B3**	**B3**	**B3**	**B3**	B4	B4	B4
Automatic traffic counters	**<u>B1</u>**	not ap.	not ap.	not ap.	not ap.	not ap.	not ap.	not ap.	not pr.	not pr.
Toll transaction data from NPRA	**<u>B1</u>**	not ap.	not ap.	not ap.	not ap.	not ap.	not ap.	not pr.	B4	not pr.
Tracking data from commercial providers	**<u>B1</u>**	not pr.	not pr.	B3	not pr.	not pr.	not pr.	not pr.	B4	not pr.
Dedicated cameras and sensors	**<u>B1</u>**	not pr.	not pr.	not pr.	not pr.	not pr.	not pr.	B4	B4	B4
Mobility-as-a-Services ordering data	**<u>B1</u>**	not ap.	B3	not ap.	not ap.	not ap.	not ap.	not ap.	not ap.	not ap.
Automatic passenger count (APC)	not ap.	not ap.	not pr.	not pr.	not ap.	**<u>B3</u>**	not ap.	not ap.	not ap.	not ap.
crowd cameras at stations	not ap.	not ap.	not pr.	not pr.	not ap.	**<u>B3</u>**	not ap.	not ap.	not ap.	not ap.

Combination of data types and unit values that are highlighted in bold and with underlying (**<u>B1</u>** and **<u>B3</u>**) are evaluation based on a full scorecard with all 19 criteria.

Combination that are highlighted in bold (but not underlined) are assessed based on all criteria, but only those criteria are discussed at deviated from previous scorecards. Combinations that are not marked bold are given underlying scores but the presentation in the main text is largely verbal.

The following unit values from the valuation study (compare section 2.1) were not considered in this assessment.

- Cancellation for Air
    - These occur quite infrequently and we do not see that travellers actually make/can make trade-offs with regards to this attribute.[13]
- Future car technology (different degree of automation)
    - This is not generally observed in real-world (in Norway). Studying partial automation (as by autopilot in Tesla) may be feasible but we do not see clear path to get the relevant data and it is unclear if there are relevant trade-offs. The relevance will increase in the future.
- Mobile coverage (PT)
    - Data on actual mobile coverage is hard to get on a departure level (for route choice) or for alternative modes (for mode choice). It is also unclear if travellers can make actual trade-offs with regards to this attribute.

3.2 Assessment criteria

We have specified 19 criteria to assess each of the included combinations of unit values and data sources. The criteria are nested in three groups.

Under the first group "Access and general quality", we assess general characteristics of the primary data, i.e. the data that is used to observed behaviour and choices. Access and required resources are evaluated from the perspective of those carrying out the valuation study. It does not included the costs and resources needed by private companies or public agencies to collect the data in the first place. E.g. RVU data is costly to collect in the first place but comes at low/none costs for researchers of the valuation study. We assess primary access/costs as of 2021, but may give a higher score in cases we know that access improve or costs reduce in the near future. This applies for app panel GPS tracking where different solutions are developed at the moment which are expected to be operational in 2022 (as the Fotefar app).

Under the second group "Opportunities for analysis for valuation", we assess how well unit values can be estimated from the primary data. This depends to a large degree on the data that can be used to quantify the attribute values of the alternatives. As mentioned earlier. this information will often come from additional data sources. In the connection, we assess the most common data sources (for current methods) or the best of the feasible data sources (for methods not yet employed). The aggregation and precision level of the primary data determines what kind of secondary data can be attached to quantify attributes. Even though some of the criteria's in this second block describe characteristics of the secondary data source, it is therefore still an important component in the assessment of the primary data source.

Contrary to the first two groups, the last group "Flexibility, synergies and future perspective" is assessed not from the perspective of the researchers specifically but from a more general perspective (including different stakeholders in the transport sector). For instance,

[13] To get an idea on (RP-based) valuation of reduced cancelation, it might be more prosperous to study the purchase of flexible tickets and/or insurance policies. This type of data and analysis is not considered in this report.

“synergies” does not involve eventual benefits for the researcher. Rather it includes the benefits of using and promoting this type of data for other application.

Table 3.2: Overview over assessment criteria

Group	Single criteria
Access and general quality	Access to relevant and updated RP data
	Resources required for data access and maintenance *(high score for low resources needed by the executing body of the valuation study; original costs by others not included)*
	Resources required for data processing *(high score for low resources needed by the executing body of the valuation study; original costs by others not included))*
	Data volume
	Coverage *(high score if all of Norway is covered)*
	Representativity
Opportunity for analysis for valuation	Observation of actual choices
	Quantification of attributes and costs of chosen alternative
	Identification/modelling of non-chosen alternatives (choice set)
	Quantification of attributes and costs of non-chosen alternative
	Variation and correlation in central attributes *(high score for high variation and low correlation)*
	Possibility to control for other effects
	Possibility to segment (current segmentation)
	Possibility for combined RP-SP models and other advanced estimation methods
Flexibility, synergies and future perspective	Possibility to frequent and continuous data collections in future
	Possibility to segment results beyond current segmentation
	Synergies with transport models
	Other synergies
	Relevance for new trends/technologies

Each combination of unit value and data type is given by a score from 1 to 5 on each of the criteria in Table 3.2. The score is briefly justified with short sentences or keywords. Section 3.4 – 3.7 gives the detailed assessments while section 3.8 provides a summary based on the (unweighted) average values of each group of criteria.

3.3 Process of giving scores

As indicated above (section 3.1), we have grouped the different combinations of unit values and data sources in blocks. The process of giving scores have been different for the different blocks.

The first block “VTTS car driver with different data sources” (section 3.4) consists of 8 data sources, i.e. 8*19=152 scores had to be given. The method for this block was based on a simplified Delphi survey among 4 researchers at TØI. In the first round, each researcher gave 152 scores without knowing the scores given by the other 3 researchers. After the first round, results where compared by the project leader and it was pointed out possible misunderstandings in the interpretation of criteria or properties of primary and secondary data sources. In round 2, each of the 4 researchers revised their own scores. In this round, the researcher could see the scores from round 1 of all researchers (but not from round 2).

In a last round, all average[14] scores (across the 4 researchers) were put in one table and inspected for inconsistencies. This lead to minor changes in the some scores.

Later in the project, further adjustments were done

- We revised some of the scores for aggregated tracking data from private companies, after we got more insights on the TomTom data
- We changed the underlying set up of the category "dedicated cameras and sensors" to make it more distinct from counting data and toll transaction data

In the second block (section 3.5), we focus on RVU data and assess the criteria data volume and representativity and the different criteria of "analysing opportunities for valuation" for each relevant unit value or group of unit value. Scores were proposed by the project leader and discussed/quality ensured by the other project participants. The scores on the remaining criteria that describe the data source (in this case RVU) more generally, are assessed to be the same for VTTS-car drivers (e.g. based on the Delphi method described above).

For the third block "Public transport unit values with data sources other than RVU" (section 3.6), a mixed strategy was used. For the data sources "automatic passenger counts" and "camera-based crowd counts" (the two data sources is not included in block 1) scores were discussed and determined after a discussion in the project team. The remaining scores in block 3 were suggested by the project leader under consideration of related scores in block 1 and 2 and quality ensured by the other project participants.

The latter also applies the scores in the last block "Remaining combinations of unit values and data sources" (section 3.7). That is, based on the previous scores, scores were proposed by the project leader and quality ensured by the other project participants.

3.4 Different data sources for car driver's VTTS

In this first block of assessment, we only consider the VTTS for car drivers, which is the most important unit value for cost-benefits analysis in general and for road infrastructure projects in particular.

We include in this list also ordering data from apps even though this is most applicable for car (taxi) passengers and for waiting time as in Goldszmidt et al. (2020) and Buchholz et al. (2020) or for micro-mobility (Johansen 2022).

In section 3.4.1, we discuss some central prerequisite for the assessment. The scorecards for the different data sources are given in section 3.4.2 to 3.4.9.

3.4.1 Prerequisites: assumed aggregation level, route identification, access to background variables and signage-effect

In this section, we firstly specify the assumed level of aggregation for the different data sources used to deriving the VTTS for car drivers. In this report, we refer to data as aggregated when observations over several car/persons are combined in one number or

[14] Mean values where used for all scores where the gap between the lowest and the highest score was lower than 3. In 5 (of 152 cases) where the gap was 3 or 4, we ones the median value instead.

statistics (typically the sum of all cars or persons). These statistics can be segmented e.g. by car type or time period, but as long as it provides combined information over several individual cars or persons, it is referred to as "aggregated". Disaggregated data on the other hand provides observations "car by car" or "person by person" and has technically a data column with a car or person identifier (ID) in the dataset.[15] Such data can also be referred to as "individual" or "microscopic" but "disaggregated" is used in the report as it is the direct antonym for "aggregated".

This is further illustrated in Figure 3.1. Data types in cell 2 and cell 4 are referred to as "aggregated data".

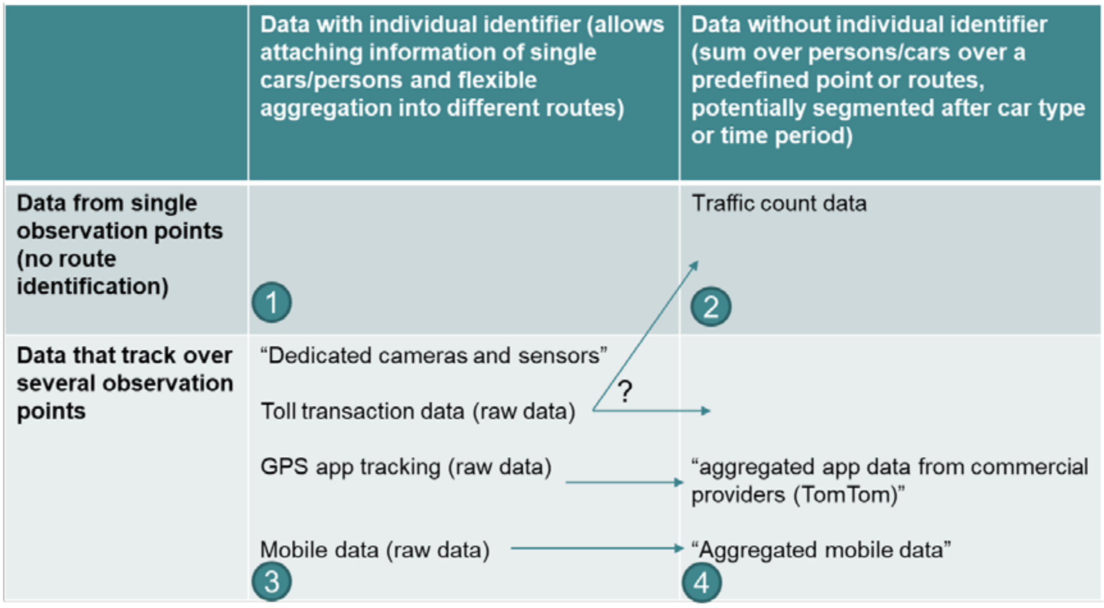


Figure 3.1: Aggregation of data for car route choice analysis.

For toll transaction data there are at least 3 possible assumptions on the aggregation level that could be made available for research:

1) The data is not aggregated at all (remains in cell 3 in Figure 10). Within this approach several precautions regarding GPDR needs to be made, but in principle it should be possible to keep this data format for research purposes
2) Data is aggregated into single observation points (cell 2 in Figure 10). In this (compact) format, the data is similar to traffic count data. An advantage over traditional count data is that information of car types could be preserved in form of segmented statistics.
3) The data could also be aggregated into predefined routes (not single points). In this case, it would be placed in cell 4 in Figure 10. As the number of routes gets (very) large with increased analysing area, it is not clear how this data set would be structured. In practice one would probably have to restrict oneself to a specific area

[15] This ID can be anonymous such that trackbacking to actual cars/persons will not be possible without additional data.

and/or a subset of possible routes. This would reduce the scope, flexibility and functionality.

For the assessment below we assume that toll transaction data is available as in cell 3. We therefor refer to it as “disaggregated toll transaction data”.

For mobile data, we assume that data can only be provided aggregated (moving from cell 3 to cell 4 in Figure 10). This seems to be the current practice in Norway. From the perspective of the researcher that is denied access to disaggregated data, this involves great inflexibility as one needs to order/pay for data a predefined format. This is costly and time consuming. From the practical example of mobile data we are aware of, the data is either aggregated into basic statistical units (BSU) or in predefined routes.

Somewhat more flexibility is provided with “aggregated app data” at least in the case of TomTom where NPRA has access to an API that aggregates results “in real time” from the disaggregated “raw data”[16]. In this solution, one does not have the option of inspecting the raw data, but can get quick access to many different results, as market shares for various routes in the network.

The data type “Dedicated camera and sensors” needs also some further explanation. In aggregated form and without keeping track on single cars it is very similar to traffic count data. When one is keeping track on single cars, it shares several aspect of disaggregated toll transaction data. To make it more distinct, we assume here that this data type gives disaggregated data and that one – contrary to toll transaction data – set up dedicated cameras (or sensors) at desired spots. In the assessment, we assume that cameras (or sensors) are set up by the research themselves and that the researchers had access to the raw data and the possibility to use ML-models that data.

Table 3.3 give and brief overview over the different approaches that are assessed.

[16] The data is likely processed and clean to some extent and therefore not “raw” in a technical sense.

Table 3.3: Overview data sources for VTTS car driver.

Data source	Assumed level of aggregation	Choice context	Secondary data to quantify attributes
National RVU	Disaggregated (trips of single persons)	Mode choice	LoS from network models
mobile data	Aggregated (BSU or routes)	Route choice (most applicable for long distance networks)	Various (e.g. google maps)
App panel with GPS-tracking	Disaggregated (trips of single persons)	Route choice (all networks)	From the add or various (e.g. google maps)
Automatic traffic counters (ATC)	Aggregated (points)	Route choice (simple networks, parallel motorways)	Various (e.g. google maps)
Toll transaction data from NPRA	Disaggregated (cars over different points)	Route choice (simple networks with road tolls)	Various (e.g. google maps)
Tracking data from commercial providers	Aggregated (BSU or routes)	Route choice (limited routes due to number of observations)	From the add or various (e.g. google maps)
Dedicated cameras and sensors	Disaggregated (cars over different points)	Route choice (limited routes due to hardware requirements)	Various (e.g. google maps)
Mobility-as-a-Services ordering data (Uber etc)	Disaggregated (trips of single persons)	Various (waiting time for car passenger most common)	Directly from the screen of the app

Within route choice, different data sources put different constraints on the complexity of the network that can be analysed. To detect routes in complicated network, one needs high precision, high frequency and disaggregated data, as it is provided in App-tracking data.

Figure 3.2 is an illustration of this. The axis in this figure are not meant to be quantitative and the positioning of the data sources is only meant for illustration. The ellipses are tilted to the right to indicate that the fidelity for a given data type typically declines with more complexity in routes/networks. This effect differs quite a bit across data types: It is expected to be very high with piecewise count data, while the effect should be minimal with disaggregated tracking data.

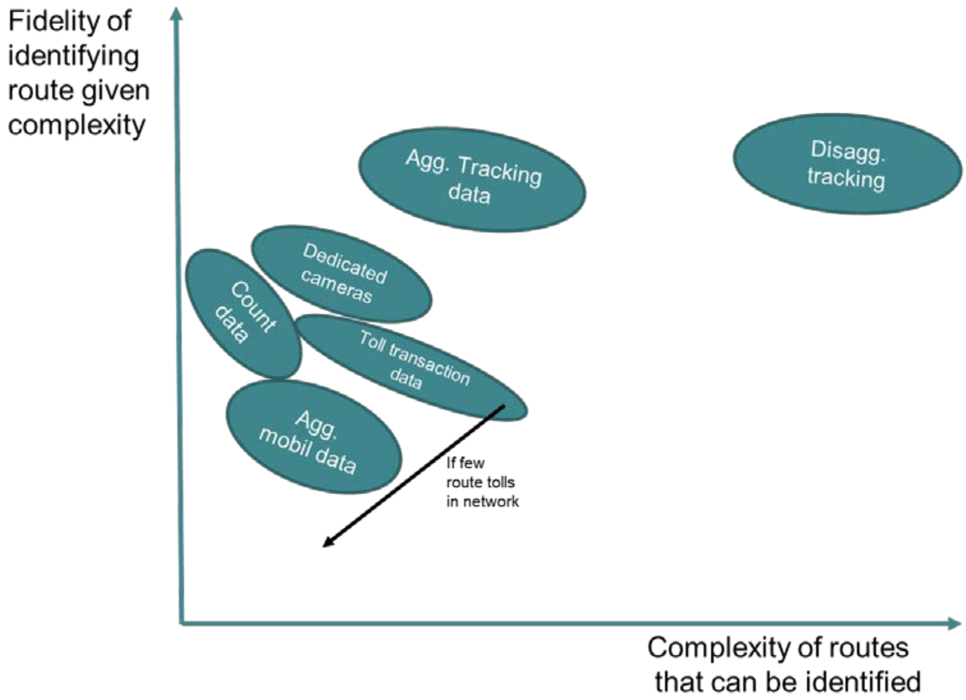


Figure 3.2: Possible route identification with different data sources.

Count data have the strongest limitation regarding the complexity of routes. Only in very simple networks and with counting points on all relevant alternatives, one can derive routes (more precisely sections of routes) with good fidelity.

Aggregated mobile data can be used in more complex routes as the raw data tracks single persons (mobil phones). However, the fidelity of mobile data is lower than for count data as observations cannot be mapped directly to roads (only to mobile cell towers). This approach is expected to work significantly better in long distance corridors.

Because of its assumed disaggregated form, Toll transaction data can in principle be used for somewhat more complex routes. However, one is highly dependent on the frequency and coverage of observation spots (i.e. road tolls). If coverage is low, analysing alternatives routes on this data source alone is very restrictive.

The same applies to "dedicated cameras", however, here one has somewhat more flexibility such that fidelity can be improved by installing more cameras.

Tracking data is clearly the most applicable data type for more complicated routes. The difference between aggregated tracking data (e.g. from TomTom) and disaggregated tracking data (e.g. Fotefar) is that aggregated data needs to be analysed in form of market shares of competing routes. This can be done with high fidelity (assuming the user group is representative), however it will be difficult to do this in complicated networks as the number of observations per route will get small if the number of routes increases.

With disaggregated (tracking) data one can analyse single observations within a discrete choice set-up, revolving the problem of having limited observations on given routes.

Access to background information on trips and decision-makers is often needed to segment results, get a more precise measure of attributes and/or to account for heterogeneity in preferences. The number of passengers is also important information. In disaggregated data analysis, this information can be used for an informative guess on what (fraction of the) road toll the car driver and the car passenger are paying. In aggregated data analysis the VTTS is only directly derived for the car as a whole. In order to infer from the VTTS of cars to the VTTS of car drivers, one needs to assume the average number of passengers per car. Travel surveys may provide national or regional averages given trip purposes, but these numbers may not be representative for specific routes (e.g. routes to locations with a lot of cabins have typically higher occupancy). An interesting approach within the method of ARNP cameras at toll stations or at dedicated spots would be to use camera and ML-techniques to observe the number of passenger or, at least, whether or not the passenger seat is taken.

Table 3.4 gives an overview over availability of variables in different data sources.

Table 3.4: Access to variables relevant for analysis

Data source	Trip distance for result segmentation	Trip purpose for result segmentation	Used car type to get correct (toll) costs	Information about number of passengers	Background information for modelling preference heterogeneity
National RVU	Available	Available	Available	Available	Available
Mobile data (Telenor, Telia)	Can be inferred (somewhat imprecise)	Not available	Not available	Not available	Not available for researchers
App panel with GPS-tracking	Available	Some apps can guess trip purpose	Not without add. surveys	Not available	Not without add. surveys
Automatic traffic counters (ATC)	Not available	Not available	Not available	Not available	Not available
Toll transaction data from NPRA	Not available	Not available (work trip may be identified with add. register data)	Available (based on amount that is paid)	Not available	Not available without add. register data
Tracking data from commercial providers	Only distributions	Not available	Not available to researchers	Not available	Not without add. surveys
Dedicated camera and sensors	Not available	Not available	Available	Cameras and ML may identify if passenger seat is taken	Not without add. surveys
Mobility-as-a-Services ordering data	Depends on specific data	Not available	Depends on specific data	Depends on specific data	Not without add. surveys

As indicated in Table 3.4, the extent to which additional data is available differs largely across the different data sources. RVU data has the widest range of information and is the only data source that has direct information about trip purposes.

Other data sources have significant limitations when it comes to additional information (unless they can be coupled to additional survey or register data). This will imply low variation in data within identified routes. Variation in aggregated data will mostly come from different periods, but this variation cannot be utilized in statistical analysis unless explanatory variables also differ in the different periods.

As discussed in more detail below, the aggregation level affects the route identification and access to background variables. It also relates to the extent that statistical analysis can be done. With aggregated data and little excess to background variables one often has very limited variation in the data, making it hard or impossible to derive more than a few parameters in the utility function describing car travellers behaviour. In particular, using aggregated counts from a few alternative routes will make it difficult to distinguish time-dependent effects from constant effects in route choice. Time-dependent effects relate to the VTTS, while constant effects related to propensity that one might prefer one route over the other, independent of the travel times.

More generally, a challenge with aggregated and low-variation data, is that one cannot statistically distinguish between different effects underlying travel behaviour. To be able to infer VTTS estimates we need to quantify the various effects that may lead a cars to take the more expensive (but faster) route.

This is illustrated in Figure 3.3, where the effects of that cars have the propensity to take the more natural routes is referred to as the “signage-effect”.

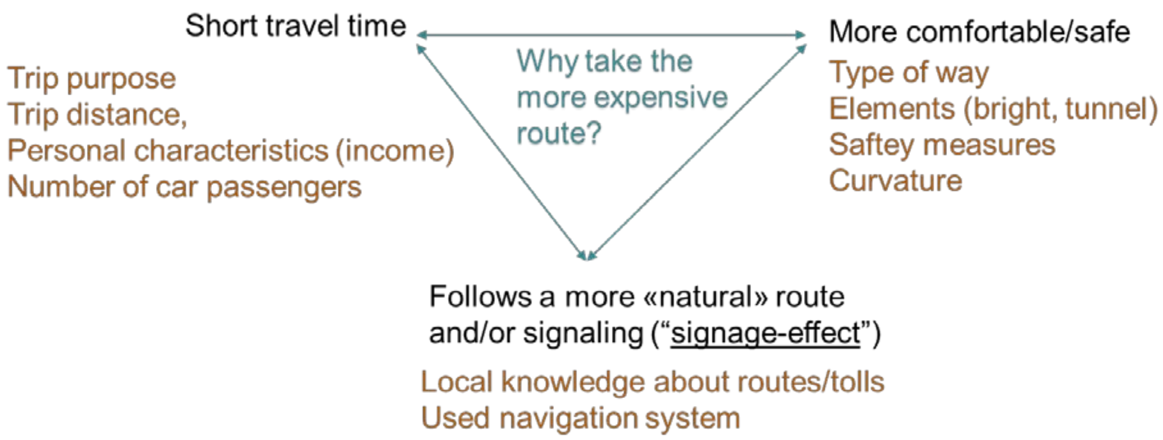


Figure 3.3: Illustration of different effects and possible dimensions of heterogeneity.

Estimating a VTTS, i.e. quantifying the willingness-to-pay to get shorter travel time, requires to control for the remaining effects (e.g. controlling for the signage-effects) and/or to segment the VTTS for different categories (e.g. the VTTS on different types of way as done by Flügel et al. (2020a).

As mentioned above, the signage-effects can be operationalized by a constant term in the utility function within the discrete route choice analysis. A positive value in the utility function of the faster route would reduce the impact of shorter travel time and lead to lower estimates of the VTTS.

3.4.2 National RVU for VTTS car driver

In this set-up, RVU data is used to model travel mode choice. The observed mode choices and the segmentation variable trip purpose are directly given by the RVU data.[17] Based on the start- and end location of the trip and the period of the day (rush or non-rush), LoS data is attached and is used to derive attribute values such as travel times. Travel costs for car are

[17] Typically, categories for mode and trip purpose are transposed/aggregated into “main” transport mode and groups of trip purposes.

estimated based on car distance (from LoS data) times a factor representing the behaviourally relevant monetary cost per km, plus road tolls. The underlying values can differ by car type if this information is available. Choice sets are defined based on background variables (drivers licence etc) and LoS variables (e.g. if access time to nearest train station is too high, train would not be included in the choice set).

It is important to note that LoS data are derived in the network models assuming a certain route choice. The route choice may or may not be consistent with the actual route choice taken by respondents.

Table 3.5 gives our assessment with some justification for each criteria. In the assessment, we implicitly assume that RVU provides 8 digit BSU codes throughout (i.e. we assume that the current practice of providing BSUs with less than 100 inhabitants with 6 digit codes does not apply to large-scale valuation studies).

Table 3.5: Scorecard for RVU data for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	4	RVU data has generally good availability for research. The most recent data goes to some sort of quality check and is therefore not immediately availability
Resources required for data access and maintenance	4	No costs for researchers and consultants. Access is bound to single projects. Some administrative burdens in connection of ordering data
Resources required for data processing	4	Some researchers (also at TØI) have wide experience with data processing of RVU
Data volume	4	Compared to some big data sources, the total number of observations is low. However the amount of background variables per observation is quite high.
Coverage (national)	4	Covers the whole of Norway. However, coverage outside the supplementary samples is likely to be sparse
Representativity	3	Some sample selection bias is likely; typically high education, high car access, low immigration background. Response rate has reduced over the years and is now at 16%. VTTS may be lower in RVU if people that are less time-constrained are more inclined to participate
Observation of actual choices	4	Transport modes reported by respondents. Researchers defines 'main' transport mode that enters the discrete choice model
Quantification of attributes and costs of chosen alternative	2	(Perceived) travel costs for cars are hard to observe/detect, travel time only segmented in rush and non-rush. General imprecision in LoS due to zonal system, and simple underlying route choice.
Identification/modelling of non-chosen alternatives (choice set)	3	Not explicitly reported, but possible to model based on available data
Quantification of attributes and costs of non-chosen alternative	2	Imprecision due to static, macroscopic model and aggregated zones.
Variation and correlation in central attributes	1	Typically high correlation. Correlation only broken in light of road tolls. Information on used car types can add variation.
Possibility to control for other effects	3	Only based on background variables and data that can be attached from the (somewhat coarse) spatio-temporal information. Little attitudinal data. On the positive side: Information on income
Possibility to segment (current segmentation)	5	Trip distance (reported and derived), trip purpose and mode choice available
Possibility for combined RP-SP models and other advanced estimation methods	2	No SP part, data volume somewhat low for some machine learning techniques

Criterion	Score (1-5)	Justification
Possibility to frequent and continuous data collections in future	4	Data collection most likely to continue in future. Continuous data collection but data not immediate available for research
Possibility to segment results beyond current segmentation	4	Geographic segmentation possible. Possibility to model VTTS as a continuous function of trip distance. No direct segmentation by user group possible
Synergies with transport models	5	High relevance for RTM estimation.
Other synergies	4	RVU widely used but not the most progressive data source.
Relevance for new trends/technologies	2	Micro-mobility not included as of 2020(!) This and other question could be added. In general: less innovative approach. May loose relevance over time in its traditional form

From Table 3.5, we see that RVU scores well (4 out of 5) on criteria related to access, costs and coverage. RVU data has some serious challenges when it comes to modelling, due to the imprecision and correlation in the LoS data used to quantity attribute values. Some of these challenges may be handle with improved transport models, better background information (car type) and better estimation techniques (see section 4.1).

Travel survey data is a very important data source with many possible synergies. Synergies with estimation of transport models stands out. This is further discussed in section 4.1.

3.4.3 Aggregated mobile data for VTTS car driver

In this set up we assume that aggregated mobile data can be used to derive market shares on simple routes in motorway networks. Deriving travel time based from google maps or similar sources, and travel costs based from road toll information, one can try to deduce the VTTS based on mathematical models (see e.g. chapter 5). Aggregated data is unlikely to facilitate statistical modelling/parameter estimation and given the lack of background information, it will be difficult to segment results within the current segmentation.

Table 3.6 gives our assessment with some justification for each criteria.

Table 3.6: Scorecard for aggregated mobile data.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	3	Possible to buy various data from private mobile companies.
Resources required for data access and maintenance	2	Rather expensive acquisitions costs (TØI payed 100 000 NOK for route data between Oslo and Hemsedal)
Resources required for data processing	3	Primary data comes aggregated and should be rather manageable in processing. Quality check might be difficult without across to primary data
Data volume	3	Based on a lot of data, but comes only in aggregated form.
Coverage (national)	3	Depends on amount of data one purchases. In most applications, data sources are likely to be restricted to certain corridors. Likely not applicable in cities (challenge of controlling for specific travel mode)
Representativity	4	Representative should be good for large mobile companies. Passive 'recruitment' avoids sample selection biases
Observation of actual choices	3	Works only in simple networks/corridors (not in cities) Routes can be observed better than with counting data. However one needs to have corridors where one is sure that only car are possible means of transport

Criterion	Score (1-5)	Justification
Quantification of attributes and costs of chosen alternative	2	Time use and costs (distance and road tolls) need to be attached from other data sources (google maps). Aggregation level likely to limit the precision of which travel times and costs can be traveler type and/or car type
Identification/modelling of non-chosen alternatives (choice set)	2	Only possible in simple networks/corridors.
Quantification of attributes and costs of non-chosen alternative	2	As for the chosen route
Variation and correlation in central attributes	2	Only variation across routes (not within). Requires that travel time and road tolls differ across the main routes
Possibility to control for other effects	1	Very difficult, the 'signage' effect is a particular challenge. One would also like to control for the number of persons in the car
Possibility to segment (current segmentation)	1	Very limited as we do not observe trip purpose. Time-of-day information may give some indications
Possibility for combined RP-SP models and other advanced estimation methods	1	No SP data and data volume (very) low when aggregation is high and/or variation low
Possibility to frequent and continuous data collections in future	5	Likely possible to buy continuous data and with high velocity
Possibility to segment results beyond current segmentation	2	Limited
Synergies with transport models	3	Low but maybe interesting for calibration
Other synergies	3	Low but may vary with the specific data set. If fine time-of-day information one might be able to infer day of time-distribution for Trenklin
Relevance for new trends/technologies	2	Limited. Cannot distinguish between micromobility (escooters) and cycle

From Table 3.6, we see that aggregated mobile data scores mediocre (2 or 3) on access, costs and coverage. Compared to RVU, this data has to be bought from private firms and we assume that it will be difficult (or very expensive) to get data set for whole Norway (at least all studies we are aware of look at single cities or corridors).

Aggregated mobile data scores rather poor on analysing opportunities as the data can – at best – be used in simplified networks and is likely to be too coarse for precise and segmented results. It is likely that variation in data will be too low to quantify the signage-effects from the data.

For long distance car travel, the precision level is not that crucial and this mobile data has some merits for analyse (compare discussion in section 5).

Mobile data scores well on criteria representative and possibility for frequent and continuous data collections in future.

3.4.4 Disaggregated App-tracking data for VTTS car driver

In this set up, high-frequency position data is used to analyse route choice in all types network. The chosen routes are identified directly from the geo-data provided by the app. The choice set, i.e. alternative routes, need to be defined. For non-trivial networks, the amount of alternative routes in each choice set need to be reduced to a manageable size. While there is an extensive literature on techniques of choice set generation in the route choice contexts, this task is not straightforward and model results may depend on the chosen method.

Precise time stamps facilitate importing time-dependent LoS data, as road tolls[18] or travel times. Travels times could be identified directly from the app, however, this can only be made real use of for modelling when precise travel times for alternative routes are available/can be important. In most cases, it is wise to import travel times consistently from the same data source (both for chosen and alternative) route, even though the actual travel time can be observed.

Table 3.7 gives our assessment with some justification for each criteria.

Table 3.7: Scorecard for disaggregated App-tracking data for VTTS car driver

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	4	Good, but currently limited to commercial data. Access to own panels likely to increase in the near future
Resources required for data access and maintenance	3	Depends on cost of recruiting respondents, costs of additional surveys and degree to which processes can be automated
Resources required for data processing	4	May initially be high as data large and complex. Can likely be automated to a large degree with own data
Data volume	4	High data volume, additional survey needed to get relevant background information
Coverage (national)	3	May vary
Representativity	3	Some sample selection bias likely (not all types of persons will take app in use and will be willing to share their movement data)
Observation of actual choices	5	Routes can be identified with high degree of detail. Most apps can distinguish cars from other transport models. May be difficult to distinguish car drivers from car passengers
Quantification of attributes and costs of chosen alternative	4	Can be detailed due to detailed spatial-temporal information
Identification/modelling of non-chosen alternatives (choice set)	3	Some challenges in defining choice sets
Quantification of attributes and costs of non-chosen alternative	4	Can be detailed due to detailed spatial-temporal information
Variation and correlation in central attributes	4	Good variation in disaggregated data. Detailed information about road tolls can be inferred to reduce correlation in attributes
Possibility to control for other effects	4	Possible to include weather information. Controlling for background variables demands information on users (may need additional surveys)
Possibility to segment (current segmentation)	3	Some challenges in identifying trip purposes from App-data (will be improved with better machine learning (ML)-models)
Possibility for combined RP-SP models and other advanced estimation methods	4	ML model may improve analysis of large data sets.
Possibility to frequent and continuous data collections in future	5	High, once initialized (and large enough panel established)
Possibility to segment results beyond current segmentation	3	Detailed geographical information may enable further segmentation (e.g. by road type). Limited background variables without additional surveys
Synergies with transport models	4	Rather low for RTM. For MATSim data could be used in the generation of travel plans and calibration of route choice

[18] Also time-dependent discounts (the Norwegian “timesregel”) can be accounted for.

Criterion	Score (1-5)	Justification
Other synergies	4	May be used as 'new'("stordata") RVUs (given additional surveys). May be interesting as a mode of paying for public transport (e.g. connected to Ruter-App). May enable new research
Relevance for new trends/technologies	5	Should be possible to detect trips with e-scooters etc. In general: a method that makes use of new technologies and analyzing methods

App-tracking data scores good (4) on current access and excellent (5) on future access and future relevance.

App-tracking data scores also good on analyzing opportunity due to the possibility for precise identification of chosen alternative and the opportunity to import precise and time-dependent attributes.

We have identified challenges regarding choice set definition and segmentation. The former can likely be solved by advance statistical methods and rigours testing/validation, the latter can likely be solved with additional surveys.

3.4.5 Automatic traffic counters for VTTS car driver

Here we assess count data (ATC) for deriving the VTT for cars as applied as Tveter et al. (2020) and (Flügel S. et al. 2020).[19] Both studies used count data from two parallel highways. For the analysis, one needs counts from both highways in the same period to derive "market shares" for the two alternative routes. One also needs to make some assumption on the actual routes cars taken (as one cannot directly observe counts from pointwise data). For example, if there are relevant locations alongside the competing routes that are not available from the other route, one should try to account for this. Without further information from other data sources, the fraction of choices that do not have actual route choices need to be guessed.

Table 3.8: Scorecard: Automatic traffic counters for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	5	Data can be downloaded freely
Resources required for data access and maintenance	5	No costs for downloads
Resources required for data processing	5	Data come in structured and standardized data sets
Data volume	3	aggregated but sizeable
Coverage (national)	4	General good coverage over Norway
Representativity	4	Passive recruitment
Observation of actual choices	2	Route not directly observed. Works only in very simple networks, typically two parallel sections of motorways. Technical difficulties to count correctly in (hyper) congestion situations
Quantification of attributes and costs of chosen alternative	2	Time use and costs (distance and road tolls) need to be attached from other data sources (google maps). As we have only aggregated data, we can't differentiate travel costs by traveler type and/or car type

[19] An alternative approach, that was mentioned in section 2.2, is calibration of VTTS within transport models.

Criterion	Score (1-5)	Justification
Identification/modelling of non-chosen alternatives (choice set)	2	Only reliably possible in very simple networks
Quantification of attributes and costs of non-chosen alternative	2	as for the chosen route
Variation and correlation in central attributes	2	Requires that travel time and road tolls differ across the main routes. We do not observe car (engine) type that could help to break correlation
Possibility to control for other effects	1	Very limited as no additional variables collected (beside time period).
Possibility to segment (current segmentation)	1	Very limited as we do not observe trip purpose. Time-of-day information may give some indications.
Possibility for combined RP-SP models and other advanced estimation methods	1	No way to identify single persons (e.g. for combined SP study). Aggregated data does not easily facilitate advanced methods
Possibility to frequent and continuous data collections in future	5	Free access likely to continue in future
Possibility to segment results beyond current segmentation	2	Generally low. It might be possible to infer VTTS differences for differ route types, when changes in tolls and counts over time can be explored
Synergies with transport models	3	Low but somewhat interesting for model calibration
Other synergies	3	Low but may vary with the specific data set. If fine time-of-day information one might be able to infer day-of-time-distribution
Relevance for new trends/technologies	2	Very limited, not very innovative approach

ATC data scores very well on access (current and future) and costs.

Unfortunately, the analysis opportunities are limited to specific cases of parallel motorways and there are several challenges to overcome (no information of car type, no information of trip purpose, signage effect).

3.4.6 Toll transaction data for VTTS car driver

As mentioned in section 3.4.1, we assume that this data will be made available in disaggregated form for research. In that case, one can track cars over multiple tolls and over a longer period. However, identifying the actual chosen route will be difficult if there are not sufficiently many tolled routes in the area of analysis.

For the analysis method, we see two alternatives. Either one does an analytical analysis of markets shares of competing routes (similar to the analysis based on count data or aggregated mobile data) or one does statistical analysis of the chosen route similar to disaggregated tracking data.

Table 3.9: Scorecard Toll transaction data for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	2	Currently not available for research, but potentially good access, as this is publicly owned data
Resources required for data access and maintenance	3	Publicly owned data, some maintenance costs will occur
Resources required for data processing	3	Researchers will need to process the data according to the specific application and empirical strategy
Data volume	4	Depends on the level of aggregation, but potentially very high
Coverage (national)	3	Toll roads are very common, with the exception of some areas. Works best in areas with frequent tolls and tolls on parallel routes
Representativity	4	Passive recruitment
Observation of actual choices	3	Can potentially track the car through multiple toll stations. Difficult if multiple routes without toll.
Quantification of attributes and costs of chosen alternative	3	Can differentiate by car type and time of day and combine with data from other sources.
Identification/modelling of non-chosen alternatives (choice set)	2	May require additional data (for routes without tolls). Can be modelled in disaggregated data analysis. In that case challenge arise regarding the choice set generation
Quantification of attributes and costs of non-chosen alternative	3	Similar to attributes of the chosen route
Variation and correlation in central attributes	2	Requires that travel time and road tolls differ across the main routes. Data differentiated by car type is an advantage.
Possibility to control for other effects	2	Depends on the aggregation level. In general difficult. Data differentiated by car type is an advantage
Possibility to segment (current segmentation)	3	Time-of-day information gives some indications. Could be combined with register data on the location of home and residence to identify commuting trips.
Possibility for combined RP-SP models and other advanced estimation methods	2	Depends on format and data volume
Possibility to frequent and continuous data collections in future	5	Data will be collected continuously with the purpose of administering toll payments, unless road tolls are abolished or replaced by a different arrangement
Possibility to segment results beyond current segmentation	4	If combined with other register data, a vast number of background characteristics can be utilized. However, we only observe the owner of the car, not the driver.
Synergies with transport models	3	May have some improvements over counting data, e.g. for calibration of time-dependent discounts ("timesregel")
Other synergies	4	Potential synergies with use of register data in research and official statistics.
Relevance for new trends/technologies	3	applies only for travel modes that use road with road tolls

Note that the scores regarding criteria related to analysis is sensitive to the assumed disaggregated data format.

3.4.7 Aggregated commercial tracking data for VTTS car driver

Aggregated tracking data count be analysed similar to count data and mobile data. The scores in Table 3.*10* are partly based on our experienced with the TomTom data, which is utilized also in chapter 5.

Table 3.10: Scorecard aggregated commercial tracking data for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	2	Possible to buy data from private companies. NPRA has access to TomTom, but sharing of data is highly restricted
Resources required for data access and maintenance	3	Depends on how data is shared
Resources required for data processing	4	Aggregated data rather easy to process
Data volume	3	Based on a lot of data, but comes only in aggregated form
Coverage (national)	4	High in the case of TomTom, but will depend on the amount of data one purchases/gets access to
Representativity	3	Specific user groups, unclear representativity
Observation of actual choices	4	Works only in simple networks / corridors (not in cities) Routes can be observed more widely and with higher fidelity compared to counting data.
Quantification of attributes and costs of chosen alternative	3	Average travel time may be directly provided. We cannot differentiate travel times or costs by traveler type and/or car type
Identification/modelling of non-chosen alternatives (choice set)	3	Only possible in smaller networks or in corridors as the number of observations per route becomes small in bigger networks
Quantification of attributes and costs of non-chosen alternative	3	As for the chosen route
Variation and correlation in central attributes	2	Only variation across routes (not within). Requires that travel time and road tolls differ across the main routes
Possibility to control for other effects	2	Limited because of aggregation level
Possibility to segment (current segmentation)	1	Limited as we do not observe trip purpose. Might be that data could be provided based on ML models from the private companies that have access to raw data
Possibility for combined RP-SP models and other advanced estimation methods	2	No SP data and data volume (very) low when aggregation is high and/or variation low
Possibility to frequent and continuous data collections in future	5	Likely possible to buy continuous data and with high velocity
Possibility to segment results beyond current segmentation	3	Limited as long as private firm do not share more background information
Synergies with transport models	3	May be interesting for calibration of route choice model
Other synergies	2	Limited. Most interesting for specific case studies where one is interested in changes in route choice and resulting changes in travel times
Relevance for new trends/technologies	3	Tracking devices in micro-mobility and future car technology might provide good data in future. Getting access to data from Tesla would be nice with respect to autonomous driving

3.4.8 Dedicated cameras and sensors

As discussed above, this data type can come in different forms. The scorecard below applies to a set up where the researchers themselves, (possibly, but not necessarily, in close cooperation with NPRA) set up cameras for research purposes. The researchers would get free access to the data within the GDPR rules. We assume that GPDR-rules can be complied with also when single cars tracked through multiple camera. In this from, routes can be identified given sufficient coverage of cameras in the network (this is likely only feasible in simple networks).

Similar to toll transaction data the analysis could either be based on aggregated markets shares of competing routes or the individual chosen route in a discrete choice set up. The latter would require sufficient variation in the data (and therefore require multiple camera installations).

Table 3.11: Scorecard for dedicated camera and sensors for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	2	Limited available access of today
Resources required for data access and maintenance	2	Hardware and installation costs may be significant
Resources required for data processing	3	Should be manageable once established (assumed data is freely accessible by researcher themselves)
Data volume	3	Somewhat limited as installation of many cameras costly
Coverage (national)	3	Likely to be limited. Method may be scaled, but cost-benefits unclear
Representativity	4	Passive recruitment
Observation of actual choices	4	Assuming disaggregated data this should work fine if cameras are well placed. Most feasible in simpler networks
Quantification of attributes and costs of chosen alternative	3	Can differentiate by car type and time of day and combine with data from other sources.
Identification/modelling of non-chosen alternatives (choice set)	3	Coverage on parallel routes critical
Quantification of attributes and costs of non-chosen alternative	3	As for the chosen route
Variation and correlation in central attributes	2	Requires that travel time and road tolls differ across the main routes. Data differentiated by car type is an advantage.
Possibility to control for other effects	3	Requires coupling to other data sources (register data)
Possibility to segment (current segmentation)	3	Time-of-day information gives some indications. Could be combined with register data on the location of home and residence to identify commuting trips.
Possibility for combined RP-SP models and other advanced estimation methods	2	Depends on data volume. If high, ML models may be interesting
Possibility to frequent and continuous data collections in future	3	Limited, but could be initialized at larger scale
Possibility to segment results beyond current segmentation	4	ML-method could identify features of car and number of passengers
Synergies with transport models	3	Calibration/validation of car occupancy
Other synergies	3	Identification of car features may enable other interesting research
Relevance for new trends/technologies	4	innovative method using recent ML techniques; could be used identify micro-mobility (if cameras placed in cities)

This data type scores somewhat similar to toll transaction data. In comparison, initial costs will be higher as we assume that cameras most first be installed. On the other hand, will one have more flexibility and presumable better coverage of data point, such that routes can be identified with greater fidelity. The approach is also somewhat more innovative and flexible. As mentioned above, both data types share the same technology, such that (relative) scores are sensitive to the exact implementation and forms of data sharing.

3.4.9 MaaS ordering data for VTTS car driver (car passenger)

MaaS ordering data (e.g. from ride-hailing services) has a quite different character compared to the other data sources. The data, as presented on the screen of the customers of the apps, looks similar to the information respondents receive in SP surveys (see Figure 2.2 in section 2.4). This allows for detailed discrete choice analysis with little/non measurement errors in central attributes.

As mentioned above most (current) MaaS apps will not include information on travel times, but waiting times. This may restrict the current application for unit values.

Table 3.12 Scorecard MaaS ordering data for VTTS car driver.

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	2	Currently not available with the required level of detail (we are only aware of the e-scooter case in Norway; Johansen 2022)
Resources required for data access and maintenance	3	Might be costly to get access
Resources required for data processing	4	Depends on data format; can be automated once initialized
Data volume	4	Disaggregated data; number of respondents depends on App
Coverage (national)	3	Likely to be restricted to certain areas
Representativity	3	Self-selection into apps likely
Observation of actual choices	5	Directly observed from the screen
Quantification of attributes and costs of chosen alternative	5	Directly observed from the screen
Identification/modelling of non-chosen alternatives (choice set)	5	Directly observed from the screen
Quantification of attributes and costs of non-chosen alternative	5	Directly observed from the screen
Variation and correlation in central attributes	3	Depends on app/case; can be enforced in 'natural experiments'
Possibility to control for other effects	3	Depends on background variables that can be coupled; good geospatial information can facilitate accounting for weather etc. One should try to control for that opening the app – and thereby the waiting time – may be endogenous (may be difficult/impossible to control for without further data)
Possibility to segment (current segmentation)	2	Trip purpose not reported
Possibility for combined RP-SP models and other advanced estimation methods	3	Similar layout with SP data, possibility to conduct additional surveys
Possibility to frequent and continuous data collections in future	4	If once available likely with frequent and continuous data collection
Possibility to segment results beyond current segmentation	3	Depends on available background information; comfort effects with taxi-car mark differs
Synergies with transport models	3	Unclear, waiting time measured differently than in RTM
Other synergies	3	Analysis may have a market value for the clients (app-owners)
Relevance for new trends/technologies	4	Somewhat innovative method; likely with new types of such data (and greater volumes)

MaaS ordering data scores below average on data access and costs. We anticipate access will get better in the future (with MaaS likely playing a stronger role also in Norway).

This data type gives excellent analysis opportunity with data precision close to SP data and (contrary to SP) real-world choices. As the decision whether to open the app at all and when to open the app (ahead of the desirable travel start) is likely to depend on the eventual choice, there are potentially problems with endogeneity. It is currently unclear how severe this problem is and how one could test/account for this.

3.5 Different unit values based on RVU

The RVU data is a holistic data set for personal travel (for persons over 12 years) as it includes all trips independent of the travel mode. It can therefore be used to model travel mode choice with an "full" choice set[20]. This allows to estimate utility function and underlying parameters for different unit values (not just for VTTS car drivers as assessed above). The amount of unit values that can be estimated is, however, limited by the LoS data that can be reliably attached to the spatial-information of start and end zone in RVU. In the current practice of deriving LoS from the RTM model system, this implies that some unit values cannot be estimated (as crowding on-board PT) and that some unit values would be estimated with rather low precision (see discussion about congestion valuation below).

Below, we give scores for 8 criteria for each of the assessed unit values (while the other criteria are assumed to be the same for all unit values).

These 8 criteria are:

- **Data volume.** The sampling of the current national RVU is not stratified by transport mode for everyday travel. This is desirable, as one can then empirically derive or statistically model market shares from the data. However, this implies that seldomly used transport modes have a lower data volume, like ferry and air[21]. This is taken into account in the scoring below. Low data volume affects the error margin of estimated parameters.
- **Representativity.** We assume that short trips are underreported in RVU[22] and that severity of this effect differs somewhat between transport modes
- **Observation of actual choices.** Travel mode choice is observed in RVU by the reported answer on questions related to "how did you travel". What is typically analysed is the "main transport mode". The clarity for which the main transport mode can be determined is likely to different across different types of trips involving different leg-modes.
- **Quantification of attributes of chosen alternative**. Differences in scores on this criterion across unit values refer to the quality of LoS data that is expected to be attached. For travel times, an assessment of the underlying route choice and speed in the LoS data is important (we expect this to be better for air, than cycle for example). For travel costs, getting the actual price may be challenging given period-tickets for PT and price discrimination for air-transport.
- **Quantification of attributes of non-chosen alternatives.** We assume that separate models are estimated for short and long distance trips. Air transport (and most ferry

[20] Minor transport modes may need to be excluded or grouped under an alternative "others".

[21] Additional question on long distance travel have a better coverage for these modes, however the data volume is still considerable lower than for car and short distance public transport.

[22] According to Harding et al (2018) trip underreporting is well-documented and relatively more prominent for short trips.

trips) would be included in long distance. The quantification of attributes for all modes (including non-chosen) is somewhat easier for long-distance trips as the underlying route choice is rather obvious (especially for air and ferry).

- **Variation and correlation.** For travel modes where the cost-function directly or indirectly includes distance, there is natural correlation between travel time and travel cost. This correlation has been a persistent challenge in estimating stable VTTS on RVU data. The correlation issue is less of a challenge for time-multipliers.

In the assessment below, we combine different modes within Public transport (buss, metro, train, tram, passenger boat) in one category as we assess their scores to be the same (and therefore join them to streamline the table and the discussion). For clarification, we repeat that we do not recommend to estimate generic unit values and one should at least test if unit values differ between the different modes. This – of course – requires that one can attach mode-specific LoS data, as done for the MPM models (Flügel et al 2015, Flügel and Jordbakke 2017).

Modelling separate utility functions for different modes, also improves the variation and reduces correlation in attribute values. We assume that this is possible when we give scores (e.g. the score 3 for “time components” is conditioned on this assumption).

Table 3.13 report the scores for different unit values. For references, we included here the VTTS for car driver for which a detailed assessment was given in Table 3.5. In the text below, we justify the scores mostly in comparison to the scores for VTT car driver.

Table 3.13: Scorecards for RVU data for other unit values.

Type of unit value	**VTTS (NOK/time)**							**Time multiplers**	
Unit value **CD: Car driver CP: car passenger W:walk, C:Cycle**	***CD***	**CP**	**PT**	**W**	**C**	**Air**	**Ferry**	**time component (PT)**	**congestion (car)**
Data volume	*4*	3	3	4	3	2	2	3	4
Representativity	*3*	3	3	2	2	3	3	3	3
Observation of actual choices	*4*	4	4	2	2	4	3	4	4
Quantification of attributes and costs of chosen alternative	*2*	2	1	1	1	3	3	1	1
Quantification of attributes and costs of non-chosen alternative	*2*	2	2	2	2	3	3	2	2
Variation and correlation in central attributes	*1*	1	2	2	2	1	1	3	1
Possibility to control for other effects	*3*	3	2	2	2	3	3	2	3
Possibility to segment (current segmentation)	*5*	5	5	3	3	5	5	5	5

Car passenger (CP) get the same score as car drivers (CD) for all categories but data volume. Data volume is considerably lower for CP, which may affect the robustness of the time parameter estimate that is specific for car passengers (if a generic time parameter is estimated for all car users, this would not apply). Assigning the correct cost attribute is challenging for CP and it depends on which assumption was applied for calculating the cost attribute of the car driver.

For the different public transport modes (buss, train, metro, tram, boat) the data volume is lower than for car driver. The quantification of the cost attribute (representing the effect of the monetary cost of a single public transport trip) is challenging due to the existence of seasonal tickets that have a fixed, but no marginal cost. An approach is to calculate an average trip cost given information about the number of trips within the period the seasonal ticket is valid for[23]. However, RVU data is lacking precise information on trip frequency by transport mode. Variation and correlation is expected to be somewhat better than for car when time attributes can be important for different kinds of public transport modes (train versus bus etc). However, high correlation will still be a challenge. When it comes to controlling for other effects, we gave a somewhat lower score (2) than for car driver, as it is not possible to control for on-bord crowding with the currently available data from RTM.

When it comes to walk and cycle, we give a lower score on representativity (2) due to likely underreporting of short trips in RVU (cf. Harding et al. (2018)). The definition of a full trip (versus trip leg) and the definition of mode choice in terms of “main transport mode” is somewhat more tricky for trips involving walking and cycling. We therefore lower the score for “ Observation of actual choices” slightly. Travel times may likely include large error margin as the zonal system is too coarse and the route choice to imprecise/generic for walk and cycle. On the other hand, correlation is less of a challenge as there is no cost attribute that can be correlated with the time attribute. Variation is likely to be low, also because walking and cycling are not available for longer trips. VTT for walk and cycle are currently segmented based on road type. This actual road type (share of road types) on the walk/cycle trips are not available from RVU. It can be derived from network models in RTM but there is great uncertainty about the quality of that data due to simplified route choice model and the zonal system which makes it impossible to know where exactly the walk/cycle trips started and ended).

Air and car ferry get similar scores than car driver. Difference being the lower data volume and the more reliable information about travel time (more obvious routes) and costs (available of ticket prices, at least average ticket prices). In case of car ferries, there may be some more ambiguity about what the main mode is.

The RVU scores of time components are similar to VTTS for different public transport modes. The challenge in terms of high correlation between time components and travel time is less severe than between travel cost and travel time. We therefor give a score of 3 on “Variation and correlation in central attributes”.

The scores for congestion are similar to the VTTS car driver. We give a lower score for “quantification of attributes and costs of chosen alternative” as congestion is not reliably derived from network models in its current form. In principle, it is possible to apply the LoS variable “travel time in congestion” and one can try to estimate the share and severity of congestion on that trip. This is likely to be rather imprecise but there may be future improvements when using more suitable transport models and/or empirical data sources.

[23] RVU contains questions about whether you have a period card, and what type. The question is not directly related to the specific journey, but it should be possible to make a rough division of public transport users after this.

3.6 Public transport related unit values with other data sources than RVU

3.6.1 Prerequisites: choice context and attribute quantification

In the previous section, we discussed some public transport related unit values for the case of mode choice modelling based on RVU data. In this section, we discuss alternative data sources for estimating PT-related unit values.

The following list sums up relevant choice context and underlying trade-offs for PT-related unit values.

1) Choice between PT (possible dived into submodes) and car, walk, cycle, micro-mobility
2) Choice between different submodes within PT (e.g. bus versus metro)
    - Trade-off between travel time (components) and ticket prices (variation in ticket prices may be low)
    - Trade-off between travel time components and invehicle travel time
3) Choice between different categories of same submode (e.g. Flytoget versus Vy)
    - Trade-off between ticket price and travel time (components)
    - Trade-off between ticket price and travel time variability/probability of delay
4) Choice between different departures/route of a given submode
    - Trade-off between waiting time and crowding (in simple networks)
    - Trade-off between travel time and crowding (in more complex networks with varying travel times from station A to B)
5) Choice between ticket type (first class, seat reservation)
    - Choice between crowding/sitting place and ticket price
6) Choice between start station (first class, seat reservation)
    - Trade-off between access time/travel time and (probability) of sitting places

The most relevant data sources for studying unit values for public transport are given in Table 3.14. The table briefly points to the expected capability of these data sources to be used as a primary data to study different choice contexts mentioned above.

For reference, we include RVU data that was assessed in the previous section. Disaggregated app-tracking and "ordering data" where discussed for the case of VTTS car in section 3.4.4 and section 3.4.9 respectively. Automatic passenger counts and camera-based crowd counts were – of obvious reasons – not included for VTTS car. These two data sources were technically described in section 2.5.6 and 2.5.7.

Table 3.14: Relevant data sources and choice context for PT-related unit values.

Trade-off from list above	1 (mode choice)	2 (submode choice)	3 (submode type choice)	4 (choice of departure /route)	5 (Choice of ticket type)	6 (choice of start stations)
RVU data	Yes	Yes	Only with access to raw data	No	Limited	Only with access to raw data
App- tracking	Yes	Yes (with advanced ML)	Yes (with advanced ML)	Yes	Not with add. surveys or coupling to ticketing systems	Yes
Ordering data	No (no data for other modes)	Yes (given that ordering data includes these type of choices)				No
Automatic passenger counts	No (no data for other modes)	Yes (given that OD-relations can be derived/estimated)			No	No
Camera-based crowd counts at stations	No (no data on for other modes)	Unlikely (needs extensive coverage of cameras)	Unlikely (needs extensive coverage of cameras)	"Wating for next departure"	No	No

Besides RVU, app-tracking data may be used to study general mode choice. The app data should in this case be able to reliably distinguish different travel modes (not just whether or not an app user is driving a car). For the remaining data sources, one will typically lack choices of other transport modes (car, walk, cycle).

Choices between submodes within public transport, types of subgroups and departures, App-tracking and ordering data may be applicable. We are however not aware of any studies that have implemented this successfully. The use of APC and camera-based crowd observation is somewhat more limited for these choice contexts. A particular challenge is that one is not observing origin-destination (OD) data with in these set-ups. In case ODs/routes are simple, (e.g. as for boat connections) the approach seems feasible. In more complicated PT networks is seems not straightforward to establish market shares on a OD level, which is needed to quantify central attributes and to observe the necessary trade-offs for analysis.

The choice of "waiting for the next departure" is relevant for camera-based crowd counts at stations (see section 3.6.3)

The choice of ticket type (reserving seating places) is mostly relevant for long distance travel. The "ordering data" as discussed earlier in light of MaaS/taxi hailing is less relevant for long-distance, but more traditional ticket sales statistics may be used for some analysis (valuation of comfort and seating places).

The choice of stations is likely only observable with disaggregated tracking data, and it might include some heavy data analysis (e.g. identifying home/work place to compute access/egress times from/to stations with sufficient precision). In general, this choice context is of less relevance for current unit values.

From the discussion, it appears that the two data sources that are not already discussed in section 3.4, i.e. "automatic passenger counts" and "camera-based crowd observation" are somewhat limited in providing data on market shares.

Table 19 gives an overview of what data sources could be used to quantify attributes of alternatives in the analysis

Table 3.15: Data types/external data sets and the possibility to quantify attributes of the chosen alternative.

	Travel time	Ticket cost	Waiting times	Headway	Travel time variability /delays	Crowding in vehicle	Crowding on station
Primary data sources							
RVU	Only self-reported	No	No	No	No	No	No
App- tracking	Yes (actual)	No	Yes (actual)	No	If measured over longer periods	No	No
Ordering data	Yes (scheduled)	Yes	As of ordering timestamp	No	No	No	No
Automatic passenger counts	No	No	No	No	No	Yes	No
Camera-based crowd counts at station	No	No	Yes, at station	No	No	No	Yes
Data sets for measuring attribute values only							
LoS data (aggr. network models)	Coarse	Averages	No (only at transfer)	Yes	No	No	No
Entur or other timetables	Yes (scheduled)	Listed prices	No (only at transfer)	Yes	No?	No	No
Real-time feeds (SIRI)	Yes	No	No	No	Yes	No	No

3.6.2 Automatic passenger counts (APC) for crowding multipliers

In this set up, APC data is used to derive market shares of alternative departures/routes possible segmented by submode. As mentioned above the identification of markets shares on a OD-level (as required to derive competing travel times) is not directly possible without tracking individuals or without additional data sources. Indirect measures as matrix balancing need to be applied if APC is used as the only data source.

Table 3.16: Scorecard Automatic passenger counts for crowding multipliers

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	4	Is continuously collected by Ruter and other PT operators
Resources required for data access and maintenance	4	Available from Ruter for selected routes, for research projects
Resources required for data processing	4	Data processing already done
Data volume	3	Aggregated but points of observation (?)
Coverage (national)	2	Not available
Representativity	4	Passive recruitment
Observation of actual choices	1	OD relations not observed , must be derived by matrix balancing
Quantification of attributes and costs of chosen alternative	2	Travel time based on OD estimation, no additional information to infer travel costs
Identification/modelling of non-chosen alternatives (choice set)	1	May be very hard to define meaningful choice sets

Criterion	Score (1-5)	Justification
Quantification of attributes and costs of non-chosen alternative	2	As for chosen mode
Variation and correlation in central attributes	2	Depends heavily on that one can observe trade-offs between travel time and crowding
Possibility to control for other effects	1	Very limited
Possibility to segment (current segmentation)	2	Trip purpose and distance not observed
Possibility for combined RP-SP models and other advanced estimation methods	2	Limited
Possibility to frequent and continuous data collections in future	5	Likely with frequent and extended data collection in future, new ML method may allow tracking
Possibility to segment results beyond current segmentation	2	Limited
Synergies with transport models	4	Validation of demand and crowding level in Trenklin
Other synergies	4	Measuring PT incentives, rush pricing schemes etc
Relevance for new trends/technologies	4	Changes in PT usage can be captured quickly

3.6.3 Camera-based crowd counts at stations for crowding multipliers

In this set up, one would use cameras to count the number of people waiting at a platform, right before and right after a metro/bus arrives at the station. The difference between "right before" and "right after" presents the number that boarded the metro/vehicle and counts of "right after" would be the number that waited for the next departure to arrive. As described in the scorecard, we presume that this measure has some significant error margins without having the possibility to track single persons on the platform (therefor the low score on "Observation of actual choices "). Despite these weaknesses, estimates of the share of waiting travellers can be used to analyse the trade-offs between crowding and (waiting) time given that knowledge of the headway (to the next relevant departure) and the crowding levels on the arriving trains/buses.

This setup only makes sense under certain conditions. In order to observe meaningful trade-offs, PT vehicle that arrive consecutively at the station need to have varying crowding and need to service the same destinations. They should probably also depart quite frequent as waiting for the next departure will likely be increasingly seldom with greater headway.

Measuring the correct crowding level of the arrive PT vehicles is another challenge. Attaching APC data is likely the best solution.

Table 3.17: Scorecard for camera-based crowding observations multipliers

Criterion	Score (1-5)	Justification
Access to relevant and updated RP data	2	We are not aware of directly accessible data in Norway
Resources required for data access and maintenance	3	Camera installation costs may be considerable
Resources required for data processing	4	Since the camera will produce numbers only data processing is quite easy
Data volume	2	Probably low, unless one can scale up camera sets ups. Works only under specific conditions
Coverage (national)	2	Some flexibility here but will be difficult to get national coverage (bus stops around Norway); meaningful only where there is congestion
Representativity	4	Passive recruitment

Criterion	Score (1-5)	Justification
Observation of actual choices	2	Without tracking persons it seems difficult to infer choices (waiting for the next departure) with high fidelity
Quantification of attributes and costs of chosen alternative	3	Expected headway (Waiting time) can be derived from timetable/real time feeds; getting the correct crowding level on the train requires additional data or extra cameras on the trains
Identification/modelling of non-chosen alternatives (choice set)	1	May be very hard to define meaningful choice sets
Quantification of attributes and costs of non-chosen alternative	2	The relevant information is here the crowding level of the first
Variation and correlation in central attributes	2	Depends heavily on that one can observe trade-offs between travel time and crowding
Possibility to control for other effects	2	No person information, same effects (bad weather) may be detectible from the camera
Possibility to segment (current segmentation)	2	Trip purpose and distance not observed
Possibility for combined RP-SP models and other advanced estimation methods	1	Very limited
Possibility to frequent and continuous data collections in future	3	Possible once cameras are installed
Possibility to segment results beyond current segmentation	2	Limited
Synergies with transport models	3	Synergies for Trenklin possible
Other synergies	4	Potentially for safety analysis
Relevance for new trends/technologies	3	Somewhat innovative method

3.6.4 Disaggregated App-tracking data for PT

Disaggregated App-data is a very rich data source that can be applied for different analysis, both from a mode choice context (including choice of type of submode) and decisions within a given PT-mode such as choice of departure and station (compare Table 3.14).

The high resolution of the data (both in space and time) allows coupling precise LoS data from secondary data sources like Entur and real-time feeds.

In order to be able to derive VTTS, one needs to estimate a cost coefficient and this seems to be most feasible – at least for short distance trips – in a mode choice/submode context.[24] For time multipliers, one does not require a cost parameter. Another advantage is that unit values are not segmented after submodes (compare Table 2.1). On the other hand, multipliers may have higher demands on controlling for other factors (that cannot fully be captured in the ASC of different modes). It seems therefore advisable to analyse choice within a given submode. Relevant choice contexts can be choice of departure and choice of station.

[24] In many cities, the ticket cost for different PT subgroups are the same (single tickets for given OD or seasonal tickets that include all PT modes) such that including car choice in the mode choice modelling is advised in order to add variation in the data.

Technically, one could estimate all types of choices in a combined mode choice/route choice model, as done in Montini et al. (2017). This is also what is assumed in the assessment below.

As we assessed disaggregated app-tracking data already in section 3.4.4, we only give scores here (Table 3.18) for criteria that vary across of different types of unit values. Note that the choice context and trade-offs are different for VTTS car (route choice where variation in cost mainly come from road tolls) and unit values for PT (combined mode/submode and route choice)

Table 3.18: Scores for disaggregated app-tracking for valuation of PT related unit values

	VTTS car (incl. for compari-sion)	**VTTS PT (short distance modes)**	**VTTS PT (long distance modes)**	**Time compo-nents (PT)**	**Invehicle crowding**	**PT Delays/ variablity**
Data volume	4	3	2	3	3	3
Observation of actual choices	5	4	4	4	4	4
Quantification of attributes and costs of chosen alternative	4	3	4	4	3	3
Identification/modelling of non-chosen alternatives (choice set)	3	3	4	4	3	3
Quantification of attributes and costs of non-chosen alternative	4	3	4	4	3	3
Variation and correlation i central attributes	4	4	4	4	2	3

Compared to VTTS car (see section 3.4.4) disaggregated app-tracking scores slightly worse for PT. The data volume will be lower for PT compared to car, especially for long-distance transport. Here it is likely that one needs a large sample of several thousand persons that donate tracking data over a longer period.

Compared to route choice with car (that only demands to map GPS observation to the correct roads), identification of observed choice (modes and departures) is more demanding for PT (we therefore give a slightly lower score for "observation of actual choices"). Similar arguments can be done (at least for short distance trips) to quantification of attributes of chosen and non-chosen alternatives.

For invehicle crowding (the trade-off between crowding and travel time) we anticipate challenges with variation and correlation: For a given line, travel time will be more or less constant (at least for boat, train and metro) such that the time coefficient needs to be estimated based on mode choice or submode choice. However, in submode choice, there will be a tendency that crowded vehicles/buses are the ones which high choice probability/market shares. This may lead to challenges in modelling and to potentially biased estimates given that one cannot sufficiently well isolate the relevant trade-off.

3.6.5 Other combinations for valuation in public transport

In this section, we briefly discuss other possibilities for unit values within public transport. The score cards are given Appendix D

1) For long distance public transport it might be possible to use mobile data to study market shares between air, ferry, long distance train and buses. For the most corridors in Norway, "competing" stations and airports are located at different mobile towers such that an identification should be possible. Mobile data scores somewhat better for VTTS for long distance PT compared to VTTS for car. The main reason for this is that observation of actual choices has more fidelity and the relatively low precision in the data is not that crucial for identifying attribute values for the chosen and non-chosen alternatives.

2) For long distance public transport, app tracking from commercial providers could also be used. Data from TomTom is lessapplicable for PT but data from fitness apps (Strava, FiBit) could be used given that they provide data over the whole day (not just when working out). For long distance travel the typically user of these apps may be more representative compared to short distance travel where users of fitness apps may be more likely to use active transport. Compared to VTTS car (which was assessed with TomTom in mind), VTTS for long distance PT based on other commercial app providers scores somewhat worst on access and cost for access, as well an data volume. We give however slightly better scores for representativity, quantification of attributes and identification of choice set.

3) If (future versions of) apps for more traditional PT (as the Ruter-app) provide information similar to MaaS-ordering data, it would be possible to use this data to study trade-offs between attributes. In the underlying assessment we give identical scores as for VTTS in the car/taxi case (section 3.4.9), except for the criteria related to the cost attribute and variation in the cost attribute, as seasonal tickets may lead to challenges in identifying average costs (unless information on trip frequency is provided). We also anticipate challenges in the statistical estimation given that there is less variation in the cost attribute across alternatives.

3.7 Remaining combinations of unit values and data sources

In this section, we discuss the remaining combination of unit values and data sources (marked yellow in Table 3.1 in section 3.1, that were not yet covered in the previous section.

3.7.1 VTTS walk and cycle with App-panel with GPS tracking

VTTS walk and cycle were assessed in section 3.5 in the case of RVU data. With current RVU data, where start- and end location are provided on the BSU level, we identified challenges in the analysis due to imprecise attachment of attributes. Other weaknesses with RVU data were rather low data volume and concerns regarding representativity.

Improvement on these criteria can be expected from disaggregated GPS-tracking as this data source has a higher resolution and more data observations (at least per person) for shorter trips.

GPS-tracking was applied to study route choice for cyclist based on the sense.dat app in Hulleberg, Flügel and Ævarsson (2018). This study estimated relative VTTS for different cycling infrastructure but could not identified absolute VTTS (trade-off between travel time and money). For this, one needs to include mode choice in the analysis. In that case, one can calculate the ratio between cycling time and a generic cost parameter that is included in the utility function of car and PT.

3.7.2 Car travel time variability

Multipliers for car time variability (VOR) are based on the trade-off between travel time and travel time variability (measured as standard units of travel time). It is probably best analysed in a route choice setting, i.e. the same choice context as VTTS car. There are several challenges in using RP data for VOR, most obviously, that information about time variability needs to be available for competing routes and for different time periods. Without discussing the (secondary) data source that the can provide this information, this aspect requires from the primary data a high fidelity in route identification and a high time resolution. We have therefore deemed most data sources as not promising (compare Table 3.1), and only considered App-panel GPS tracking and dedicated cameras and sensors. Both data sources have high time resolution and high fidelity in route identification (assuming good coverage of cameras). If data is collected over a longer period, these data sources could also provide estimates of travel time variability for competing routes, at least in simple motorway networks.

There are some more fundamental challenges regarding the use of RP for car time variability.

a) There is a natural correlation between road congestion and travel time variability, and it may in practice be hard to isolate the two effects. The idea to separate the two effects in appraisal is to valuate changes in driving comfort to the multiplier for road congestion, while the multiplier for VOR is meant to capture uncertainty with respect to scheduling.
b) For direct trade-offs between travel time and time variability, the faster road needs to be the one with the higher standard deviation. While this is likely true for some circumstances (a faster route will attract more cars, and therefore be more prone to congestion), it is unclear to what extent such trade-off are really detectable, given that in many areas in Norway, congestion is low and reliability presumably high.
c) The causality between variability (and congestion) and demand (i.e. route choice) goes in both directions: Congestion and low reliability has a negative effect on demand, but high demand also results in congestion and low reliability. In valuation, we are (only) interested in the former.
d) In light of modern navigation system, the trade-off between travel time and travel time variability, may not be real, as the fundamental uncertainty in travel times is largely reduced on a trip-to-trip basis.

We have not enough experience to judge the merits and severity of these challenges. We therefore given largely the same score as for VTTS car for the two data sources. We have only reduced the score for “possibility to control for other effects” to account for the challenge regarding separating out road congestion. On the other hand, the current unit values for VOR are not segmented by trip purpose. The score for “possibility to segment results” are therefore slightly higher.

Independent of these changes in scores, app-tracking is overall assessed as more promising as dedicated cameras and sensors.

3.7.3 Road congestion

The discussion for road congestion multipliers is similar to the one for VOR in the previous section. Attributes quantification is arguable somewhat easier than for VOR. We therefore include also disaggregated toll transaction data and aggregated tracking data from commercial providers (provided that market shares can be provided with a time resolution of at least "rush versus non-rush period"). Note also that we have assessed congestion multipliers for mode choice based on RVU data (section 3.5).

Similarly to VOR in the previous section, we slightly reduce the scores for "possibility to control for other effects" and slightly increase the score for "possibility to segment results".

Again, disaggregated GPS data is assessment as the overall best approach. The other data sources score similar on analysing opportunities.

3.7.4 Reduced insecurity of avalanches

To the extent that (car) routes differ in the actual risk for landslides, it is possibly to estimate trade-off against travel time and/or travel cost. An example could be a road toll in a tunnel, while the competing free route is prone to landslide risk.

Several challenges for estimating landslide risk with RP can be anticipated. The question on the correct quantification of actual landslide risk on competing routes is a topic of its own (and relates more to secondary data sources). For the primary data, a more fundamental questions is whether or not observed marked shares can be related to difference in landslide risk at all, and if so whether or not one has sufficient variation in the data to statically isolate the effects.

We see two approaches to get a data base with enough variation: First we could use GPS-tracking data over larger areas (preferable whole Norway) to get variation in data. Secondly, one could focus on specific areas and use dedicated cameras and sensors to observe route choice. Data from one spot (one pair of competing routs) is likely not sufficient as the variation in data will probably not suffice to statically isolate (control) for other effects, e.g. that the road more prone to landslide is also the more curved and more uncomfortable to drive on.

The two data sources have different advantages that coincide with the advantages for other unit values: GPS-tracking data has generally higher precision data and more data volume while dedicated cameras have an advantage of passive recruitment (no sample selection bias).

3.8 Summary of assessment

In this summary section, we discuss the total score for the three groups of criteria that we assessed for all 10 major data types. Total scores are calculated as unweighted averages of scores[25] of single criteria.

3.8.1 Data access and general quality

Data access and general quality was assessed based on the following criteria:

- Access to relevant and updated RP data
- Resources required for data access and maintenance *(high score for low resources needed by the executing body of the valuation study; original costs by others not included)*
- Resources required for data processing *(high score for low resources needed by the executing body of the valuation study; original costs by others not included)*
- Data volume
- Coverage *(high score if all of Norway is covered)*
- Representativity

While the latter three criteria may depend on the unit value of interest, the total scores for this group of criteria is rather stable across different relevant unit values.

Table 3.19 gives the total score for data access and general quality, together with some major advantages and disadvantages.

Table 3.19: Total scores for data access and general quality (Total score for most applicable unit value).

Data source	Total score	Main advantage	Main disadvantage
National RVU	3.9	Good availability and coverage	Somewhat limited data volume and unclear representativity
mobile data	2.8	Presumable low sample selection bias	Rather expensive acquisition costs
App panel with GPS-tracking	3.5	Large data volume	Rather high (initial) costs and representativity may be somewhat compromised
Automatic traffic counters (ATC)	4.1	Good accessibility; no sample selection bias	Somewhat limited data volume due to aggregated nature
Toll transaction data	3.2	No sample selection bias; potentially high data volume (in disaggregated form)	Currently not available for research
Tracking data from commercial providers	3.0	Data comes in tailored format via API	Rather expensive acquisition costs. Unclear representativity
Dedicated cameras and sensors	2.7	No sample selection bias	Limited access of today; high initial costs
Mobility-as-a-Services ordering data	2.9	Potentially high data volume	Currently not available
Automatic passenger counts (APC)	3.5	Good accessibility; no sample selection bias	Unclear/limited coverage
crowded cameras at stations	2.8	No sample selection bias	Not accessible at the moment

[25] While scores were rounded in the scorecards, we used unrounded ("original") scores when calculating averages. Original scores can have decimal numbers as a result of the Delphi method.

Data from automatic traffic counters (ATC) scores best on "access and general quality" as it free data, that is easy to process and it has good coverage and no problems with sample selection bias.

Data sources that have currently limited access (dedicated cameras and sensors, Mobility-as-a-Service ordering data and crowded cameras at stations) and/or are expensive to acquire (mobile data and tracking data from commercial providers) score below average.

A significant plus for some of the Big Data sources that are based on passive sensing is that they are not prone to sample selection biases.

3.8.2 Opportunities for analysis for valuation

In this section we give an overview over total scores for Opportunities for analysis for valuation. Analysis relates here solely on the estimation of unit values with current segmentation.

The criteria for Opportunities for analysis for valuation were:

- Observation of actual choices
- Quantification of attributes and costs of chosen alternative
- Identification/modelling of non-chosen alternatives (choice set)
- Quantification of attributes and costs of non-chosen alternative
- Variation and correlation in central attributes
- Possibility to control for other effects
- Possibility to segment (current segmentation)
- Possibility for combined RP-SP models and other advanced estimation methods

The total scores can vary with the underlying unit value and we report the range of total scores in the following sum-up table (*Table 3.20).* Besides the total scores, an important information is also how many unit values the data source in applicable for. This information, which is in reference to Table 3.1 in section 3.1., is also given in *Table* 3.20.

Table 3.20: Number of applicable unit values and range of total scores for Opportunity of analysis for estimation of unit values.

Data source	Number of unit value data is applicable*	Total score	Main advantage	Main disadvantage
National RVU	6	2.2- 2.9	Covers current requirement for segmentation	Imprecise spatial information
mobile data	2	1.7-2.1	Somewhat better control over routes compared to ATC, at least for long distance	Little control and possibility for segmentation; works poorly for short distance routes
App panel with GPS-tracking	10	3.3-3.7	Detailed information on routes	Trip purpose unreliable observed
Automatic traffic counters (ATC)	1	1.6		Routes not directly observed
Toll transaction data	2	2.6	Can distinguish car types	Works only in networks that contain road tolls
Tracking data from commercial providers	2	2.1-2.3	Better control over route than mobile data and ATC	Little background information
Dedicated cameras and sensors	4	2.7-2.9	Good control over routes given good sufficient coverage of cameras	Trip purpose not observed

Data source	Number of unit value data is applicable*	Total score	Main advantage	Main disadvantage
Mobility-as-a-Services ordering data	2	3.5-3.8	Direct and precise information on attribute values	Trip purpose not observed, open the app likely endogenous
Automatic passenger counts (APC)	1	1.6		OD not directly observed
crowded cameras at stations	1	1.9		Works only under specific conditions

*This is with reference to Table 3.1. The maximum number is 10.

Mobility-as-a-Service ordering owns the high score for analysing opportunities (3.8). In an optimal scenario, this data source provides direct and precise information on relevant alternative. In current form however, it is unclear for which unit values it is actually applicable. There are also some questions regarding endogeneity which may compromise analysing opportunities. Further research should shed more light into this.

App panel with GPS-tracking is applicable for 10 groups of unit values and scores generally high on analysis opportunities. The main reason being that the high spatial and temporal resolution of the data, allowing to identify routes with high fidelity, also in complicated networks.

National RVU can be used to study mode choice and to estimate several unit values. Advantages being good information on background information such that one can accommodate current requirements for segmentation. The spatial information on the data (available for research) is based on the level of BSU, which is rather coarse for short distance trips and can lead to imprecise quantification of attributes (see also the discussion in section 4.1).

The rather high score for toll transaction data is conditioned on an assumption that this data can be shared in disaggregated form (e.g. with a identifier that allows tracking over several road tolls and potentially couple it with register data). In aggregated form and without tracking, the data would have scores similar to ATC (below 2), and in case of aggregated tracking data it would have in the range of aggregated mobile data and aggregated tracking data, i.e. around a score of 2.

Note that, APC score rather poorly on analysing opportunity. This mainly relates to the current incapability of identifying OD-relations. This could be improved when cameras can (technically and legally) track persons over the entire PT-trip or if APC data can be combined with other relevant data sources.

3.8.3 Flexibility, synergies and future perspective

The last group of criteria encompasses flexibility, synergies and future perspective of the data sources. As described in section 3.2 this group is assessed from a general perspective and not from the perspective of the researchers (as the two previous groups). The following criteria where included:

- Possibility to frequent and continuous data collections in future
- Possibility to segment results beyond current segmentation
- Synergies with transport models
- Other synergies

- Relevance for new trends/technologies

Table 3.21 gives the total scores. Note that these scores are independent of the underlying unit value.

Table 3.21: Total scores for flexibility, synergies and future perspective.

Data source	Total score	Main advantage	Main disadvantage
National RVU	3.5	synergies with RTM	not very innovative approach
mobile data	2.6	continuous/frequent data collection also in future	Limited for further analysis/segmentation/ new transport forms
App panel with GPS-tracking	3.9	different other application (research and commercial)	further analysis/ segmentation may depend on additional surveys
Automatic traffic counters (ATC)	2.7	continuous/frequent data collection also in future	Limited respect to other analysis/segmentation and less innovative approach
Toll transaction data	3.6	continuous/frequent data collection; interesting synergies especially when combined with register data	applies only toll-paying traveller
Tracking data from commercial providers	3.0	future improvements likely	limited segmentation and synergies
Dedicated cameras and sensors	3.3	innovative method with potentially wide range of application, observations of passenger seat occupied	no large scale data collection planned
Mobility-as-a-Services ordering data	3.2	relevant for future MaaS solutions	needs add. surveys to achieve synergies
Automatic passenger counts (APC)	3.8	continuous/frequent data collection also in future; interesting for other analysis (incl. quantify crowding)	Some synergies limited due to lack of background variables
crowded cameras at stations	3.0	May be interesting for other studies at station (safety)	Unclear future access, limited/specific synergies

App panel with GPS-tracking have the widest range of possible synergies, including establishing of travel plans for agent-based simulation models (MATSim). For many synergies however, additional surveys are crucial.

Automatic passenger counts score well on “flexibility, synergies and future perspective” due to good future access and relevance for PT- relevant transport analysis.

Toll transaction data and national RVU data score also well here. They are important data source and have several important synergies. However, both data sets are somewhat less innovative in current form and score below average on relevance for new trends/technologies.

3.8.4 Overall ranking

Figure 3.4 gives an overall ranking of the evaluated data types. The scores for opportunity for analysis for valuation apply to the unit value with the best score within each data type.

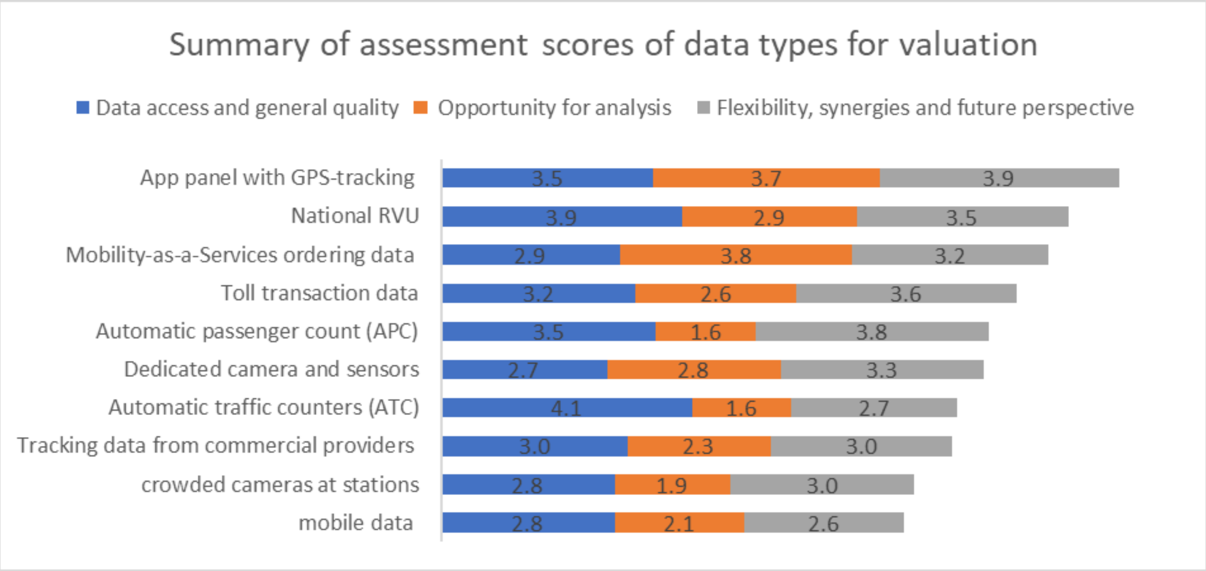


Figure 3.4: Overall ranking of data types for valuation

App panel with GPS-tracking is ranked highest overall. It is further discussed in the next chapter. The next chapter includes also national RVU and toll transaction data, two data sources that also rank high in our assessment.

4 Illustration of most promising approaches

In this section, we discuss three of the most promising approaches under a more practical perspective. This is done by going through the following 6 questions:

1) Where do you get the data from?
2) How much does it cost?
3) Are there restrictions with GDPR?
4) What are success factors in connection to data processing and analysis?
5) To what extent do we expect better results from RP data (compared to SP data)?
6) What could be concrete synergies?

Before answering these questions, each approach is introduced and motivated in a bit more detail.

4.1 RVU estimation with possible combination with RTM estimation

4.1.1 Introduction

RVU was earlier described in section 2.5.2 and was evaluated for the use of different unit values in section 3.5 (and for VTTS for car driver in section 3.4).

RVU data is a natural candidate for establishing unit values for project appraisal as it is also used to establish the regional and national transport models that are widely used for transport planning and cost-benefit analysis in Norway.

The regional transport model system (RTM) covers trips up to 70km. Its demand model (TraMod_by), consists of models for car access, trip generation and a combined model of mode and destination choice (MD-model). These models consist again of different submodels. The MD-model for instance is segmented into different trip purposes.

The MD models include implicit willingness-to-pay values in the utility functions of different modes (and destinations). For some trip purposes, the underlying parameters of the VTTS had to be fixed to the official values at that time (estimated in 2009 from SP data), because direct estimation from RVU data gave unreasonable estimates. The main challenge was high correlation in time and cost attributes in the underlying LoS data (see more in section 4.1.5), making the estimation of VTTS very sensible to the transformations of attributes and other specification of the utility functions.

The RTM estimation was based on RVU data from 2013/2014. RVU data from 2018/2019 is the latest data from a normal situation, i.e. without influence from the corona pandemic. Data from RVU 2020 is also accessible, while 2021 RVU is currently under quality assurance. Due to the pandemic, data from these years will likely be less relevant for deriving preferences for long-term transport planning.

In this approach, one would align the estimation of the next RTM-model (or an reestimation of the existing one) with the new/updated valuation study. The mode choice utility function within the MD estimation in RTM are compatible with the RVU-estimation approach assessed earlier in the report. [26]

The subsequent section discusses practical issues, success factor and possible benefits of this approach.

4.1.2 Where do you get the data from?

Commissioned by the Department of Transport and the transport authorities, the RVU data from 2016-2019 was collected by Epinion. It is – in anonymized form (see section 4.1.4) – distributed by the Public Road Administration (NPRA) on behalf of the transport authorities.

Researchers and consultants need to apply to NPRA to get access to the data. In practice, this is done by sending an email to Oscar Kleven (we are not aware of a more formal procedure).

A data processing agreement needs to be signed by NPRA and the executing research entity. The data use is limited to a specific project and to specific persons involved in the project, and must be deleted after the end of the project period.

4.1.3 How much does it cost?

The RVU data is distributed free-of-charge by NPRA.

4.1.4 Are there restrictions with GDPR?

RVU data contains personal information, both background information (incl. income) and detailed information of sequences of trips. All data is self-reported and respondents can choose “do not want to answer” for personal questions.

As mentioned above, the RVU is distributed in anonymized form, i.e. it does not include names, contact information and home and work addresses of the respondents. In the processed data set, the geographical locations are given in basic statistical unit, (BSU , “grunnkrets”) that are reported by 8-digit codes. In later years (likely due to the GDPR introduction in 2016), locations for BSU with lower than 100 inhabitants are not given by 8-digit codes but by aggregates of BSU that come in 6 digit codes.

[26] As described in section 2.2, RVU data (as of today) is most applicable for estimating unit values based on travel mode choice. Information on route choice is not available and information on departure time choice is too coarse (reported in full hours). In travel mode choice, the VTTS (in monetary terms) for a given travel mode is estimated (implicitly) by the ratio (invehicle) time and cost parameter included in the utility function of the corresponding travel mode. By the token (“a dollar is a dollar”), the cost parameter is typically assumed generic for all modes. For free-of-charge travel modes (walk and cycle) the VTTS is estimated by the specific time parameters and the generic cost parameter. Other unit values (time multipliers) can be derived by the specific time parameter (access time, waiting time, …) and the invehicle time parameter.

4.1.5 What are success factors in connection to data processing and analysis?

In mode choice estimation based on RVU data, or travel survey in more general, the following success factors can be mentioned:

- Increase variation and decrease correlation in the central attribute values. This can be achieved by
  - Being able to distinguish the used car types and assign correct road toll reductions (most Norwegian road tolls are free for el-cars as of today)
  - Attaching time/congestion-dependent travel times and (if applicable) time-dependent road tolls and ticket prices.
  - Distinguish between regular bikes and e-bikes in assigning of travel times
  - Information on the travel party and information how travel costs are split between car drivers and passengers.
- Increase general precision in LoS variables.
  - This may be achieved by improving the route choice model in the underlying LoS data production, potentially using other (more fine-grained and dynamic) transport models.
  - It is very important that researchers get access to all BSU as 8 digit codes. The use of 6 digit codes would further increase the imprecision in LoS variables.
- Gather sufficient information for choice set generation. One can try to get a better sense of the actual car availability for a certain trips. Information about driver's license and general car access in the household alone may not always represent the actual car access in a given situation.
- (Better) controlling for otherwise unobserved effects (as parking restriction at destination; crowding on PT, weather conditions, travel party etc.)
- Rigorous statistical testing of different specification in the estimation model. The method developed by Varela et al (2018) may improve estimation precision.

As the RVU data is neither tailored for RTM estimation nor for VTTS estimation, there might be venues for adjusting the current RVU or conduction a separate survey. A separate survey tailored for joint RTM/VTTS estimation could overcome some of the shortcoming of the current RVU data. Improvement could be done regarding

- Higher precision of spatial information of the trip (start coordinates, end coordinates, station for transfers) beyond BSU 27
- Possible information about actual route choice or characteristics of the chosen route (if there were tolls, what cycling infrastructure and so on).
- Information on the available alternatives (for choice set generation)
- Better information on used ticket types and frequency of travel with seasonal tickets
- Better information of control variables (see above)

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[27] This data is available in the original RVU data, but is removed from the anonymized data files that are provided to researchers.

In addition, a tailored survey may facilitate to include some SP choices (for RP-SP estimations) and/or invitation to donate additional data (e.g. app-tracking data).

4.1.6 To what extent do we expect better results from RP data?

The general purpose of RP data is to avoid the hypothetical bias of SP data. The approach of estimating based on RVU data is a feasible option for that, also when the goal is to estimate national unit values.

RVU data has similar challenges compared to SP data when it comes to recruitment and possible sample selection biases.

The precision and robustness of the VTT estimates based on RVU data will be highly dependent on the quality of LoS data that can be attached to the mode choice. If LoS data has sufficient high variation and precision, one can expect good and reliable estimation results, also after segmenting into current segmentation.

The approach is challenging for unit values that are currently not captured in the utility functions of the RTM model, such as crowding costs. Crowding costs are difficult to quantify without precise information on the chosen/available departures and without a transport model that can estimate the extent of crowding.

4.1.7 What could be concrete synergies?

Synergies with transport models is an obvious advantage of the described approach. A successful joint estimation will increase the consistency between demand prediction (via RTM) and user-benefit calculation within cost-benefit analysis. The current inconsistencies, i.e. a demand model based on RP and unit values based on SP data, have long been discussed and criticized. The suggested approach can be a way to resolve this issue.[28]

4.2 Fotefar Tracking app with recruitment from large samples

4.2.1 Introduction

The Fotefar framework is a transport mode detection (TMD) and location tracking system that can be implemented in mobile phone applications. It is currently under development by Epigram AS, Fotefar AS and TØI. The TMD includes public transport (can distinguish between bus/tram/metro/train), car, bike, e-scooter and walking. It is not restricted to any infrastructure (e.g. Bluetooth beacons, wifi access points) besides the standard sensors in current smartphones.

The main reason why TØI decided to develop their own app rather than pick one of the commercially available alternatives was that they want a transparent scientific tool, where the scientists are in control of all steps of the data value chain.

[28] Some inconsistencies may be warranted. E.g. there are argument been made that the VTTS for business trips should be different in demand modelling and in appraisal.

The Fotefar standalone app can be used for panel studies of up to several thousand participants. A pilot study with 1000 participants is planned for the first quarter of 2022, as part of a research project financed by the Norwegian Research Council (NRC research project number: 283321). Here, detailed travel information will be accessible to the researchers.

The Fotefar framework can also be included in ticketing apps, where it can measure the transport mode and distance travelled, and calculate the required ticket fee automatically. In principle, this can be done on the handheld device, without any data leaving the handset. However, statistical data might be transferred to the PTA. The detail of the data transferred can be set by the user.

In a research context, it is possible that the users can donate their data to research. The user then gives informed consent to the data being used for research, and the level of detail of the data can be set. For example, the user can decide to share the number of trips and total distance travelled per time interval (day/week/month). Or she can decide to share the data in very high detail, including timestamps and all trip location information (routes).

Another possible use case, given broad adaption in e.g. ticketing systems, is the possibility to anonymize the data in a similar way than is done by the mobile phone companies (*k*-anonymity): One can query the dataset how many people travelled from A to B within a certain time frame. However, one will only get a valid answer if the data of more than *k* users is contained in this query. This way, no individual can be identified from the data. This anonymizing method is currently applied by the major telecom companies in the context of mobile phone data, and allows to give insight into flows of people from one place to another, without exposing the individual data.

4.2.2 Where do you get the data from?

A panel study can be conducted by TØI.

If the data comes from a ticketing application, Entur might be in a good position to be data owner.

Another possible venues for recruitment at-scale could be the NAF membership register or participants of the national RVU-survey.

4.2.3 How much does it cost?

For a panel study, recruitment and onboarding will be the driving factors. A panel of 1000 participants might require 50,000–100 000 NOK.

If the framework is used in a ticketing app, some costs to incentivise data sharing in form of ticket subsidies might be necessary.

If the framework is widely adapted and the data can be anonymized and accessed, the cost will be relatively low.

4.2.4 Are there restrictions with GDPR?

In the case of panel studies and users sharing their data, the users give informed consent to use the data for research purposes. With that, GDPR requirements should be satisfied.

The data may also be anonymized using e.g. *k*-anonymity and other methods, which means that there will be fewer restrictions on sharing data with others.

4.2.5 What are success factors in connection to data processing and analysis?

One weakness for App panel GPS tracking is potential sample selection bias, i.e. some underlying and widely unobserved mechanism that make the sample not representative for the whole population. Good recruitment strategies are therefore important.

The high resolution enables coupling detailed Level-of-Service data. Dependent on the data volume and the complexity of the network that is studied, it might be possible to use direct data on travel times and travel time variability as input to the analysis.

4.2.6 To what extent do we expect better results from RP data?

Route choice analysis based on SP data is very abstract and stylized. To not overload the cognitive requirements one typically presents 2-6 attributes of 2-3 alternative routes and assumes that everything else is identical between the routes. Besides the general hypothetical biases, there might be unintended framing effects that can lead to an overfocus of certain attributes in SP. The RP approach has clear advantages here, and app panel tracking data such as Fotefar are the preferred data type due to the high fidelity that routes can be identified, even in complex networks.

4.2.7 What could be concrete synergies?

Besides valuation, there are a wide range of potential synergies and further analysis .

- Tracking data generates more data and provides more detailed data than traditional travel surveys based on questionnaires. Incorporating tracking data as part of national or regional travel surveys are therefore promising approach. We are aware of some tests by the transport authorities ("StordataRVU").
- With a continuous data collection of a sufficiently large sample and automated analysis, it should be possible to detect detailed changes in travel behavior, e.g. due to upcoming pandemic or other shocks to the transport sector.
- The detailed data of whole-day travel patterns could be used as source of deriving agent plans for agent-based transport models such as MATSim.
- Combined with ticketing, one could get investigate last mile choices and travel chains, as well as fare elasticities.
- In a panel study, it might be possible to have mini surveys triggered by location or mode choice, asking questions about alternatives and reasons for the choices.
- Detailed data is in particular relevant for short distance trips and this type of data is there highly relevant for studying micro-mobility.

4.3 Toll transaction data for research

4.3.1 Introduction

Toll transaction data was earlier described in section 2.5.8 and was evaluated for the use of different unit values in section 3.4.6.

The potential of this data source is so far under-utilized in transport research. A notable exception is the study by Isaksen and Johansen (2021) of the introduction of congestion pricing in Bergen. They use toll transaction data to measure traffic volume, aggregated to 15-minute intervals. Similar data is also used in the evaluations by the Norwegian Public Roads Administration (NPRA) of changes in the tolling schemes in Oslo and Bergen (Presterud, 2018a; Presterud, 2018b).

An advantage of toll transaction data compared to data from the automated traffic counters (ATC, section 2.5.6) is that information about price and traffic is collected at the same geographic point, while ATC sensors are not necessarily placed where road tolls are collected. In an evaluation of new toll gates in Bergen, Norconsult (2020) note that traffic count data is not available near some of the new toll gates, or that data quality is inferior. When using traffic count data, one will notice that the coverage is often reported as low. In toll transaction data, coverage is high, as the purpose of the system is to register all vehicles that pass the toll station. The disadvantage, of course, is that data is only collected on toll roads and not on other roads.

The potential of this data for estimation of unit values (and travel choice modelling in general) depends on the level of aggregation. In principle, it is possible to (1) track the same individual on different days, (2) track the same individual through multiple toll gates or (3) based on the vehicle plate number, combine data on travel behaviour with characteristics of the vehicle owner (or household of the owner) from administrative registers. The latter type of data is also relatively under-utilized in transport research (Fevang et al., 2021) However, such applications are relatively ambitious and require that good systems and routines are in place for handling and giving access to data.

4.3.2 Where do you get the data from?

Toll transaction data is collected by the toll companies (Fjellinjen, Ferde etc.). In their study of Bergen, Isaksen and Johansen (2021) received data directly from the toll company Ferde. However, to our knowledge, this data is now only available through the data owner, the NPRA. We do not know what policy the NPRA currently has regarding giving access to the data for research purposes, but to our knowledge, access has not been given to any projects.

4.3.3 How much does it cost?

As the NPRA has not yet given access to such data, we do not have information on what it would charge. Presumably, the costs of the NPRA of providing this data would be higher than in the case of RVU data, where less processing is required. Still, the cost should be manageable. When having a data sharing platform in place, the costs will be negligible.

4.3.4 Are there restrictions with GDPR?

Toll transaction data is similar to other data from administrative registers in the sense that individuals have not given their active consent to using this data for research. Access to such data is mandated by an exemption in the Norwegian data protection legislation that applies to research or statistics purposes. Rich individual-level data from administrative registers have been used extensively in research, for instance in labour economics and education research, but to a lesser extent in transportation research (Fevang et al., 2021). In many cases, Statistics Norway is responsible for giving access to the data on behalf of the registry owner. Statistics Norway also uses registry data for producing official statistics.

In principle, toll transaction data could be made available on the same terms as other registry data, even individual-level data. However, as for other data sources, the benefits of more detailed and disaggregated data must be weighed against the cost in terms of privacy concerns. Extensive data on the travel patterns of individuals that can indirectly be identified can be regarded as quite sensitive. The trade-off between scientific value and privacy must be made on a case-by-case basis.

A *k*-anonymity approach, as applied for mobile network data (2.5.3) and described in section 4.2 could allow usage of relatively detailed data, without compromising the individual's privacy.

4.3.5 What are success factors in connection to data processing and analysis?

The potential of this data source for estimating unit values depends on (1) the level of aggregation and (2) to what extent the data can be combined with other data from administrative registers. From the road transaction data itself, the following information would be useful:

- Data segmented by vehicle category, including all categories that pay different toll rates (small cars, heavy trucks, diesel, gasoline, electric, hydrogen, electric vans etc.). This is critical information.
- Data segmented by time-of-day, preferably 15-minute intervals. This will make it possible to study choice of departure time with time-differentiated toll rates (congestion pricing)
- Data on frequent and non-frequent travelers, which combined with day and hour can be used to identify different trip categories
- Dissaggregated (individual) data, i.e. data combining transactions at multiple toll stations, which gives better information on the trip and route choice

By combining the toll transaction data with data from other administrative registers, the following useful information could be extracted:

- More detailed data on vehicle type and characteristics
- Characteristics of the owner (or owning household) of the car, like age, income, family status, labor market status etc. Of particular interest would be characteristics that are commonly used to explain variation in unit values in other approaches (e.g. SP studies)

- Location of residence, workplace and second home (cabin etc.) of the owner (or owning household) of the car, which can be used to identify trip purpose. If trip purpose can be identified with reasonable certainty, a complete characterization of the trip (length, travel time, cost etc.) is possible, including characteristics of alternative routes and modes.

It should be emphasized that researchers do not necessarily need all this information in combination. Different research questions require different information. This is also the case with traditional register data, where researchers apply for the data that they need for their specific project and state in the application why they need this particular information.

4.3.6 To what extent do we expect better results from RP data?

The advantage of this data and RP data in general is that there are no concerns regarding hypothetical bias. One such potential concern is that respondents in SP surveys pay more attention to the cost attribute than they do when making real-world choices. This would lead to an underestimation of the VTT.

However, the fact that RP choices are real do not imply that they are necessarily rational in the classical sense. It could also be that travelers in some cases systematically underestimate the cost if the cost is less salient, for instance in the case of automatic toll collection (Finkelstein, 2009). In that case, it becomes an open theoretical question whether unit values estimated based on such behavior should be applied in CBA. Recent changes in the toll systems in Oslo and other Norwegian cities would be interesting to study in this respect.[29]

The other main advantage of toll transaction data that might produce better results than SP data is of course sample size. The drawback is that one might not have the variation necessary to estimate all unit values of concern and at the same time be able to correct for other factors affecting the valuation. This again partly depends on the level of aggregation.

4.3.7 What could be concrete synergies?

Toll transaction data could also be used to answer other research questions within transport economics, for instance issues related to the use of pricing instruments to mitigate external effects of transport. Although this purpose is not always stated explicitly, road tolls are one of the key policy instruments for reducing car traffic in urban areas. In several cities, road tolls have developed in the direction of congestion pricing, with higher rates during rush hour (Isaksen and Johansen, 2021). Updated knowledge on how these policies work is needed, also in light of potential changes in travel behavior during and after the Covid-19 pandemic.

Two closely related topics are distributional effects of road tolls and political opposition. In order to assess the distributional effects and to what extent these can explain political opposition, we need information about how different individuals or groups are affected by

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[29] Hypothetical bias might not only affect the cost attribute. It could also be that respondents underestimate the discomfort of time spent traveling when answering an SP survey. Halse et al (2021) find some suggestive evidence pointing in this direction.

the policies and how they adjust their behavior. Toll transaction data would be highly suitable for studying this.

As for other registry data, there are also synergies between using the data in research and for official statistics. Statistics production requires data processing and verification that would also benefit researchers, and new research findings could lead to new methods being used in the production of statistics.

5 Pilot: case study Sandvika- Hemsedal

The aim of the case study was to investigate if we can use mobile data to derive VTTS in car for trips between Sandvika (near Oslo) and Hemsedal[30]. Hemsedal lies around 200 km north-west of Oslo and is a popular destination with many hotels and cabins.

We depart from data set that TØI has bought from Telia in 2020. In the process we discovered that other data sources (TomTom) could be used to supplement our analysis. Description of data and derived market shares

5.1 Mobile data from Telia

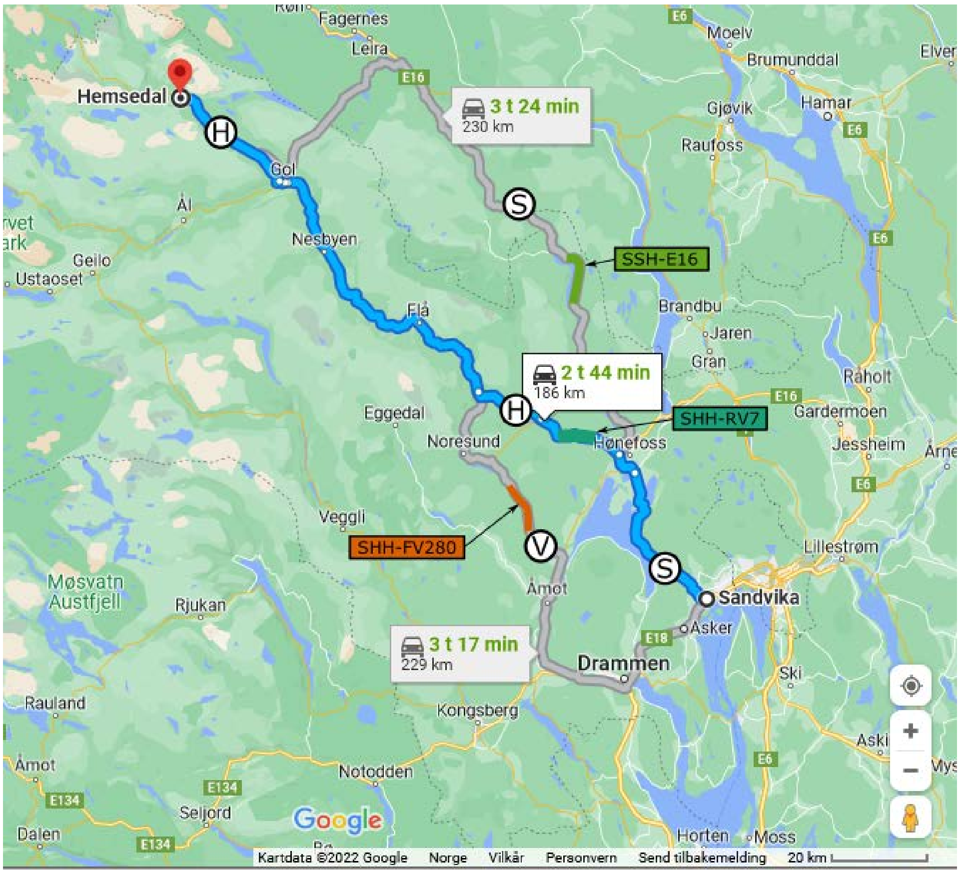

Figure 5.1: Three different routes Oslo-Hemsedal. Source: GoogleMaps

In 2020, TØI started a process to buy a set of mobile network data from Telia Norway. The case study was aiming to measure the number of people travelling from Oslo to Hemsedal via three different routes (see Figure 5.1) during the autumn vacation (week 40) in 2019. In

[30] This was one of 4 possible pilot project we suggested to the client. More information can be found in Appendix B.

addition to the route data, the flow of people passing Sollihøgda (North-west of Oslo, marked with "S" in Figure 5.1) on E16 should be compared to an automated traffic counter.

The routed dataset contains people that started in Oslo, passed one of the three stretches marked in Figure 5.1 and ended in Hemsedal municipality. A dwell time of 50 minutes was allowed, so shorter breaks at energy stations would not break the trip. Longer stops however cause the trip to be lost from the data set.

For the routed dataset, daily aggregates were formed. This was done to satisfy anonymity criteria: If a certain set of parameters yields a result containing the information from less than 5 individual persons, the result is omitted. In order to get a satisfying number of results on the alternative routes, the daily aggregation per route was chosen. Since the longer route alternatives via FV280 and E16 are chosen less frequent than the main route via RV7 (see also Figure 5.3), even the daily aggregation leads to days with less than 5 individual persons. Therefore, these routes yield data mainly in the weekends.

Due to the daily aggregation, no information about the distribution of the data throughout the day is available in the routed data set.

For the flow dataset at Sollihøgda, network counts are aggregated per hour. The anonymity requirement leads to some losses in the night hours. Here also the ATC data shows little to none traffic.

The mobile network dataset (MD) presents its counts as "people": The cell tower connections are corrected for IOT-devices (e.g. connected cars) and the marked share in the geographical region.

Figure 5.2 shows the distribution of people on the three different routes for a period of four weeks around the autumn vacation (week 40) in Oslo in 2019. Clearly, the route SHH-RV7 is the preferred route for both directions. On Fridays in week 38 and 39, a lot of people travel towards Hemsedal, and seem to come back on Sunday. For week 40, however, the traffic bound to Hemsedal is spread more through the week. The amount of people travelling back to Oslo on Sunday is a factor 1.6 higher than the Sunday before.

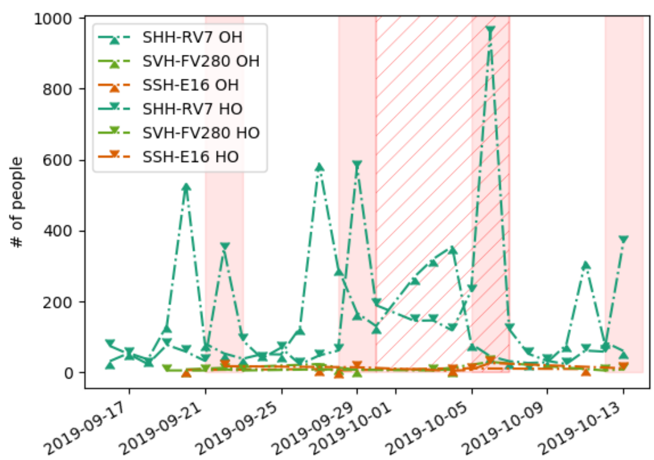

Figure 5.2: Number of people travelling between Oslo and Hemsedal on 3 different routes, according to the mobile network data set. The light red bars mark weekends, the hatched area marks the autumn vacation in Oslo in week 40. The triangular marker pointing up denotes the direction Oslo-Hemsedal (OH), the marker pointing down Hemsedal-Oslo (HO), respectively. The dash-dotted lines act as a guide to the eye.

The share of people travelling the longer routes SVH-FV280 and SSH-E16 is calculated as an aggregate over the four weeks and presented in Figure 5.3. As already expected from Figure 5.2, the marked shares are low, ranging from 1.0 to 2.0 %.

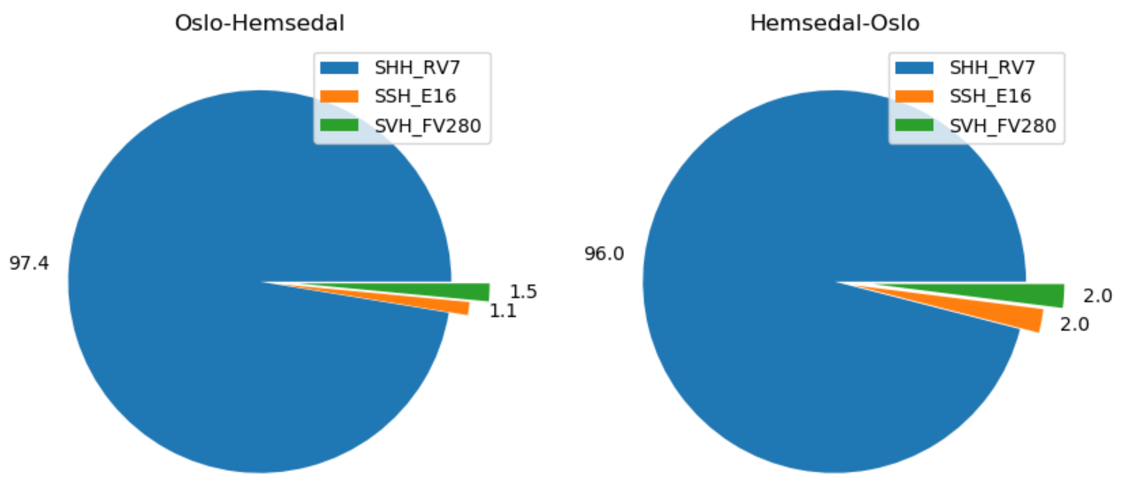

Figure 5.3: Market shares derived from the mobile network data, for each direction and route.

5.2 Route choice data from TomTom

In this section, we briefly discuss route choice data from TomTom. TomTom data is commercially available in Norway and contains information from 2008 onwards.

The NPRA has access to a flexible API, where – besides other things- route choice information can be extracted. The data analysis in this section was not performed by TØI directly but by our contact person at NPRA. In order to use the resulting route choice data in this report, TØI had to buy the rights to this analysis.

TomTom collects positioning data from vehicles with a TomTom navigation device. These are mainly built-in devices that are installed by the OEM (original equipment manufacturer). In addition, we have been informed that TomTom has bought and integrated GPS data from (undisclosed) smart phone manufacturers.[31] The use of such GPS data is likely to correct for some of the sampling bias that would otherwise result from only including vehicles with a TomTom navigation device.[32] A forum entry by a TomTom employee on the TomTom

[31] Email correspondence with Joachim Viktil (Rambøll).

[32] As an example: We are not aware that Tesla is supporting TomTom navigation devices, at least not built-in. Tesla drivers are therefore less likely to be included in the TomTom sample. In case the share of data coming from smartphones is sufficient large this biases may be minimized given that the smart phone manufacturers cover a large share of the market. In order for this to hold, it seems important that data is provided by the biggest companies (as Apple and Samsung). However, we do not have this information as the smart phone manufactures are undisclosed.

community website states that TomTom "usually observe up to 15-20 % data penetration on highways and major roads".[33] However, we are not sure that this applies to Norway.

As indicated by our contact in NPRA, the API does not distinguish between freight and personal transport.

The data on route choice does not include the pilot case period in 2019. We therefore estimate the VTTS from more recent data on a sub-case area: On the way from Oslo to Hemsedal/Hallingdal, the tolled Ørgenviktunnelen on RV7 between Sokna and Ørgenvika can be bypassed by a 20 minute longer detour via Noresund (FV288 and FV280, see Figure 5.4).

The current setup of the TomTom analysis package that the NPRA has subscribed to, will allow us to measure the share of vehicles that left RV7 at Sokna, drive via Noresund and rejoin RV7 at Gigernes. This includes all vehicles, i.e. not only vehicles driving specifically from to/from Hemsedal.[34] We therefore refer to the directions as "west " and "east ".

The table below shows derived marked shares of the detour via Noresund. The share 1.42%[35] is used in the calculation in the next section.

Table 5.1: Market share of detour via Noresund from TomTom data

Fra TomTom	Share via Noresund
West (Thursday–Sunday)	1.15%
West (Monday–Wednesday)	2.03%
East (Thursday–Sunday)	0.85%
East (Monday–Wednesday)	2.15%
Weighted average	1.42%

33 https://devforum.tomtom.com/t/tomtom-traffic-stats-in-scientific-research/2304 (accessed 30.4.2022)

34 Note that the underlying API uses a dwell time of 20 minutes to define a trip as ended. This may be a too short time window in order to detect whole trips between Oslo and Hemsedal. Refueling stops increase travel time, and we only find very few trips that drive the whole distance without stops.

35 The weighted average is based on the total number of observations. We are not allowed to report these numbers in the report.

Figure 5.4: Example of screenshot from TomTom-API "Fra Hønefoss" includes all vehicles passing from the east, "Mot Hemsedal" is the same amount of vehicles (in contrast to the counts from mobile data, these are not only trips ending in Hemsedal, but all trips headed north/west on RV7).

5.3 Deriving VTTS

In this section, we show how we can use mathematical models to derive an estimate for VTTS based on the observed route choice behavior.

The mathematical model assumes that market share (P) for a given route k can be described by function (1).

(1) $$P_k = \frac{e^{\mu * G_k}}{\sum_j e^{\mu * G_j}}$$

Where μ is the typical scale parameter of logit models and G_k is the generalized cost for route k. As higher generalized cost lead to lower market shares, μ is expected to be negative.

G_k is further specified in equation (2).

(2) $$G_k = \beta_k + c * D_k + B_k + \omega * T_k$$

Where

β_k: is an alternative specific constant of route k. In the calculation below, we assume $\beta_k = 0$.

c: is the kilometer cost of driving. In the calculation below we assume $c = 1\ NOK/km$.

D_k : is distance in km of route k. It is given in Table 5.2 below.

B_k: is the toll after discounts for route k. It is given in Table 5.2 below.

T_k: is the average travel time of route k. It is given in Table 5.2 below.

ω: is the generic VTTS of one car

Table 5.2: Data input to mathematical model

Route (index k)	Marked share (%), main routes	Split at Halling-porten	Marked shares all	Split 2	Road toll before discount (NOK)	Travel time (min)	Distance (km)	Assumed E-car share (%)	Toll after discount
1: SHH-Rv7	1.55%		1.55%		56	201	231	10.0%	40.32
2: SHH-E16 (via Hallingporten)	96.70%	98.58%	95.33%	98.2%	78	159	187	15.5%	52.73
2: SHH-E16 (via Noresund		1.42%	1.37%		0	179	207	5.0%	0
4: SVH-FV280	1.75%		1.75%	1.8%	0	195	220	10.0%	0

In a first analysis, we derive the VTTS (ω) from the market split at the Hallingporten., i.e. we find the value of ω that is consistent with the empirical route choice behavior (98.6% taking the faster road toll and 1.42% take the longer and free route via Noresund).

In the case of two routes and the assumption of $\beta_k = 0$, we can use the mathematical model (equation 1 and 2) to analytically derive a function for VTTS (ω) given an assumption on the scale parameter and observable explanatory variables. This function is given in equation (3), here for k=2,3.[36]

(3)
$$\omega = \frac{ln\left(\frac{1-P_2}{P_2}\right) - \mu * ((B_3 - B_2) + c(D_3 - D_2))}{\mu * (T_3 - T_2)}$$

Market shares across two routes contain one point of observation (as the market share of the second wrote is always 100%-share of the first route). From one observation, it is not possible to identify both ω and μ.

Assuming $\mu = -0.024561594$, the value estimated in the case study Arendal-Tvedestrand (Halse et al. 2022b), the resulting ω would be 10.27 NOK/min, which corresponds to a VTTS of 616 NOK/hour. This value seems a bit on the high side but may still be plausible given the scenario, i.e. medium/long-distance trips, high occupancy in cars and wealthy sample given that it is quite expensive to rent/own cabins in Hemsedal/Hallingdal.

VTTS estimates are sensitive to assumptions of market shares and scale parameter as Table 5.3shown

Table 5.3: Calculated VTTS (NOK/hour) given different assumptions of mu and route choice split at Hallingporten.

Assumed route split	95-5	97-3	98-2	99-1	99.5-0.5
mu=-0.02	540	620	682	787	892
mu=-0.0246	457	523	573	659	744
mu=-0.03	393	446	487	558	628

[36] See appendix C for the derivation

In a second analysis, we compare the SHH-E16 (via Hallingporten) against route SVH-FV280. In this scenario, the time gain from the faster SHH_16 route is higher (36 minutes) compared to the scenario with the Noresund detour (20 minutes). This implies that the same modal split will give lower VTTS estimates. Combining information from mobile data and TomTom, the mode split is calculated at 98.2% versus 1.8%. This yields an VTTS estimate of 304 NOK/hour. Doing the same sensitivity analysis as in Table 5.3, the value would range between 196 NOK/hour and 474 NOK/hour.

We have also tried to derive VTTS when taking more than two routes into consideration simultaneously. We could not find an analytical solution in these cases, but using a numerical "least square error" analysis, we found a VTTS around 560 NOK/h, i.e. closer to the value obtained from the split at Hallingporten.

5.4 Discussion of case study

The case for avoiding the Ørgenviktunnel via Noresund is hardly representative for general route choice behavior. It was rather chosen as a case to demonstrate the conceptual method of deriving VTT from RP route choice data. The following caveat should be mentioned if one attempts to generalized the results to other areas or to national unit values:

- The detour requires local knowledge of the possibility
- The detour requires actively leaving the main route (RV7) and taking off to FV288 (this relates to the signage effect)
- The detour is a quite a short leg compared to the whole trip Oslo-Hemsedal
- People travelling on weekend trips to Hemsedal usually have above-average income
- The market shares are pretty extreme (only 1.42% do take the detour). There might be unobserved reasons for some few travellers to take the longer routes. Note that trips that include shopping or eating in Noresund are likely to be eliminated by the low dwell time in the TomTom data.

In addition, our analysis has some weaknesses:

- The analysis assumed no signage effect, which might not be realistic (see above). More variation in data is needed to statically infer an eventual signage effect.
- We imported a value for scale parameter from a related study. Preferably, one would estimate it from the same data
- The mixed data strategy is not optimal in our case. We could have gotten information about the route split at Hallingsporten from mobile data from Telia aswell but decided against paying for this additional data. The low usage of the detour cause a lot of missing data, since days with less than 5 observations would have been truncated from the mobile data set.
- Aggregated data allows only to model "average" behaviour. With disaggregated data, or at least more segmented aggregated data, the following could be identified
    - Car type (important to assign correct road toll to each choice)
    - Exact OD and more detailed timestamps (my help to guess trip purpose)
    - Occupancy per car/car type
    - Distance distribution (both Telia data and TomTom data should be able to provide such data. One can also derived such distributions from transport models)

6 Conclusion and Discussion

6.1 Conclusion

Below we summarise our main conclusions:

1) As of today, travel surveys such as **national RVU** are the most relevant data source with regard to the current segmentation of unit values which require information about travel purposes. There are large potential synergies with transport models and one should consider aligning the next RTM estimation with the next valuation study. In this connection, it may be appropriate to move away from the current RVU, and rather design a more tailored survey that is better suited for both demand modelling and valuation.
2) **Data from apps that can track individuals** with GPS or other high resolution/frequency sensors score overall best in our assessment. The ability to add background information is important. This may require additional data collection, for instance in form of surveys.
3) **A combination of surveys (and/or register data) and GPS tracking is considered the best option and something that is recommended to work towards.**
4) **Aggregated data** (e.g. counting data on roads and public transport) place great constraints on analysis opportunities and will hardly be sufficient for national unit values given requirements coverage and in the current segmentation. That said, it can – based on appropriate case studies – help to validate the absolute level of the value of time (VTTS).
5) Aggregated **mobile data** provides better analysis options compared to counting data, at least for intercity travel, but is quite expensive to get access to. As other aggregated data sources it has clear limitations compared to more disaggregated data sources.
6) **Toll transaction data that tracks individual cars** will be able to provide information of route choice of individuals or groups in areas with a good coverage of road tolls and there are different possibilities to add individual background variables. Such data would in most cases not be completely anonymous, but access to non-anonymous data for research purposes would most likely be feasible under the current data protection legislation. However, facilitating access to data would require some goodwill and effort of the owners of the data. A more flexible (but more expensive) alternative to this data is to set up **dedicated cameras for automatic number plate recognition** (ANPR).
7) **Aggregated App-data from commercial enterprises** can also be a promising alternative. NPRA has access to aggregated tracking results from TomTom, a data source which could be utilized more for the studying route choice behaviour, e.g. at toll roads across the country. In order to use TomTom data for research, access to more information about data collection and data processing, and the possibility the share this information with the public, are crucial. There are currently also major limitation in sharing data and publishing results from data analysis.
8) Most data sources mentioned under 4) – 7) have a fundamental advantage in their passive recruitment. The data sources are therefore interesting for the quality

assurance of survey and app-based studies where unobservable factors can affect the level of the VTTS due to sample selection bias. That said, there can also be some biases in the sample of mobile companies and app-data providers.

9) A disaggregated data source with great potential are **MaaS ordering data** (e.g. from raid-hailing services). It is currently limited in access and application. In Norway studying choices/preference for micro-mobility seems most applicable. This type of data might also be made available via future versions of more traditional PT apps (e.g. via a future version of the Ruter-app that may let travellers pick, order and pay for all available transport solutions).

6.2 Discussion and perspective

In the last 20-30 years, the field of non-market valuation and transport valuation in particular has been dominated by the use of stated preference methods. The following trends are likely to contribute to a shift (back) to revealed preference :

1. Consistent criticism of the SP method
    a. General doubts that SP results have external validity
    b. No convincing solutions or refusals of SP artefacts (i.e. design choices by the researcher that impact results)
2. It appears more and more difficult to recruit respondents to participate in surveys, especially in long and demanding surveys (as SP surveys). Getting a sufficiently large and representative sample is therefore increasingly costly.
3. Evidence from the latest Norwegian value of time study indicate that (unobserved) sample selection bias might be a significant challenge, at least for VTTS estimates (Halse et al. 2022a) [37]
4. Various Big Data sources are already available or will be available in the near future for Norwegian transport research.
5. Most Big Data sources are continuously collected and have a high velocity. This implies that the amount of data is steadily increasing
6. Quality of processing and analysing (Big) data is likely to further improve in future
    a. This includes (Big) data fusion that seems underutilized at the moment
    b. Identifying trip purpose (being essential to unit value segmentation) is likely to improve with further developments in data processing, augmentation and machine learning algorithms
7. Road tolls (providing observable trade-offs between time and money) are likely to persist in Norway

[37] A statistical within-sample comparison in that papers shows that the recruitment method has significant impact on the VTTS results. People recruitment from internet panels (or in general those respondents that are members of an internet panel) have significant lower VTTS than respondents recruitment in field and/or those not being active panel members). This suggest that people that are generally willing to spend time answering surveys have lower VTTS. Within-sample difference can be accounted for by weighting results, but a fundamental concern is the VTTS of those persons that decline to participle. Big Data studies (with passive recruitment) and additional short surveys asking “are you a member of an internet panel” may shed some light into this question.

8. The future is likely to get more complex and dynamic. Hence, boundary conditions and also preferences may change more rapidly. In this connection, the typical time interval of large national valuation studies of 8-10 years may be regarded as too large. Automatically collected Big Data sources can be a way towards more frequent updating of unit values. We also believe that large parts of the analysis can be automated, which would enable more continuous tracking of preferences over time.[38]

The following caveats and challenges with respect to RP and Big Data should be mentioned:

1. RP surveys (as travel surveys) and GPS tracking have similar challenges regarding recruitment and potential biases. An advantage of passive GPS tracking is that it does not require time from the respondents (once installed), thus making it less prone to unobserved sample selection bias with regard to time use and VTTS estimation.
2. RP data do not exist for future attributes. For the valuation of not-yet-existing attributes (like "level 5" vehicle automation), the SP method is likely the only viable option.
3. Using less structured data (Big Data compared to SP data) makes it in general more difficult to observe relevant trade-offs, model underlying decision-making and estimate the isolated effect of attributes. High correlation and low variation in data might still be a major challenge to overcome in RP/Big Data valuation.
4. Some unit values will be hard to estimate based on RP data. Besides future attributes mentioned in 2) and econometric challenges mentioned in 3) this applies to situation where benefits come in bundles and where it is difficult to isolated separated effects. This applies for example to valuation of reduced congestion and the valuation of reduced travel time variability. In order to statically control and separate out both effects one needs data where the two attributes (congestion and reliability) vary independently from each other, at least to some extent.[39]
5. When Big Data sources are used to study route choice of cars, it is not possible to directly estimate the VTTS of car passengers, as only the behaviour of the car driver is revealed. From most analysis one does only get the VTTS for the car as a whole and assumptions needs to be made on how to break down the "VTTS for a car" in the VTTS of the car driver and the car passenger(s).
6. Some privacy/GPDR issues remain somewhat unclear and need to be treated with caution
7. From a more philosophical perspective, there might be concerns that the "private" behaviour observed in RP choice does actually not precisely reflect the public preference of inhabitants. One might argue that many car drivers in Norway are not (fully) aware of driving costs/road tolls that they are (remotely) paying for. In that case the trade-offs they appear to make when choosing a toll road in favour of the slower free road may differ from the trade-offs they would do as a member of

[38] While this may not be immediately necessary for cost-benefit analysis (that assumes stable preference over time), it may be very interesting for transport modelling and policy making in the more short-term (tactical) perspective.

[39] The SP method has clear advantages here as one can introduce systematic variation in the data via the experimental design.

society, e.g. when they would be asked to vote over different infrastructure project with given price tags (compare discussion in Mouter and Chorus (2016).

6.3 Uncertainty and further research

The assessment in this report represents the knowledge and judgment of the project team as of March 2022.

There is a lot of activity around Big Data, both in Norway and internationally. With the scope of this project it was impossible to get a full overview and it is likely we have overseen some project and opportunities in Big Data technology and analysing possibilities.

We believe that the rise and improvement of Big Data will continue in the future. This implies a danger that some of our assessment will be outdated in relatively short time. However, we believe that the broader discussion is useful also given changes to data access and quality over time.

Same aspects of the assessment were hard to judge from outside, e.g. without having seen the actual data sets and without having done the actual testing of the (estimation) method. We tried our best to incorporate our own experience, the experience and knowledge of our colleagues and that what could be inferred from the international literature.

We have assessed the different data types one-by-one. We want to point out that combining different data types may be prosperous, especially when the combined data types supplement each other and mitigate weaknesses of single data types. An example are automatic passenger counts (APC) that would score significantly better on “analysing opportunities” once OD-relations could be inferred with high fidelity; this might be possible if additional data sources are used in combination.

This report is meant as an overview report. We recommend to conduct follow-up studies that concentrate on specific data types (or combinations of data types) and give room for more empirical tests.

6.4 Practical recommendations for next valuation study

In a final section of this report, we want to recommend new approaches for the next valuation study.

Despite the uncertainty described in the section above, we do think that one can point to some viable solutions. We are confident that the following recommendation are robust in the (near) future.

We see three approaches for the next valuation study. They are given below in ranked order.

1) **GPS-tracking data plus background surveys**. The recruitment should come from a combination of large (existing) samples[40] or – preferably – the population register. Economic incentives should be given for donating tracking data to the project as this is likely to attract a broader sample and can therefore reduce the danger of sample

[40] As from the Ruter-app, the NAF register or the RVU-sample as in the pilot “StordataRVU”

selection biases. From a modelling perspective, combined mode and route choice models are likely to give the best and broadest basis for unit value estimation. The background survey should include questions on mode, car type and ticket type availability and include information about the location of home, work and other points of interest of respondents such that trip purpose can be derived from the spatial information in the GPS data. In addition, small SP experiments could be included in the background survey for cross-validation and for estimation of unit values that may be difficult to estimate from RP data.

2) **National RVU or – preferable – a tailored travel survey[41] in a joint estimation with the RTM model.** Compared to suggestion (1.), this approach puts less weight on precise data and emphasizes consistency and synergies with transport models. The unit values would be derived from the mode choice utility function of the mode/destination choice models that are part of the RTM model system (se section 4.1). Fitting route choice models in the network assignment tool (e.g. CUBE) against aggregated data sources can in addition support the estimation/recommendation of unit values.[42] It is highly recommended that spatial information from the travel survey data is provide with 8 digit BSU codes throughout (i.e. annul the current practice of providing BSUs with less than 100 inhabitants with 6 digit codes). With that, the level of precision will still be far below GPS-tracking, but should be acceptable within this approach.
3) A third approach would be to **keep the stated preference** approach. In this case, we would recommend **to use several well-crafted RP case studies to validate/adjust the overall level of VTTS.** Combined RP-SP models would be recommended in order to utilized the advantages of both data types. In this connection it would be preferable to recruit part of the SP sample from the areas where the RP case studies are conducted.

[41] See section 4.1.5 for a discussion.

[42] From a cost-benefit perspective, consistency between (implicit) valuation in the route choice models seems at least as important as consistency with the demand model.

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Appendices

Appendix A: Additional literature

Literature overview on Big Data and public transport by Zannat and Choudhury (2019).

Table 1: Review of studies on big data for travel pattern analysis in PT planning. Source: prepared by the author, 2019.

	Article	Focus	Data used	Key findings
Aggregate vs. individual travel behavior	Zhao et al.[77]	Proposing a methodology to predict daily individual mobility and testing the method using smart card records from more than 10,000 users in London, U.K. over 2 years	Smart card data	Promising results obtained, which shows the proposed method can predict daily travel behavior and accuracy varies by the attributes considered
	Zhang et al.[75]	Developing a method to identify group travel behavior (GTB) of the PT user using 1-week records of subway fare card	Smart card data	Proposed method and smart card data have the potentiality to describe the characteristics and the spatio-temporal pattern of GTB
	Briand et al.[14]	Proposing a generative model to regroup PT passengers based on their temporal habits using smart card information collected for 5 years	Smart card data	Proposed unsupervised clustering method (Gaussian mixture model) makes it possible to model continuous representation of temporal travel pattern using smart card data
	Kieu et al.[36]	Developing an algorithm to understand individual passenger travel behavior using smart card data of 4 months period	Smart card data	Proposed Weighted Stop Density-Based Scanning Algorithm with Noise (WS-DBSCAN) algorithm is able to detect the daily changes in spatial travel pattern using smart card data with lower computation time
	Chu and Chapleau[21]	Proposing a method to enhance transit trip characterization by adding a multiday dimension to a month of smart card transactions	Smart card data and AVL data	Proposed rule-based algorithm and classification enables multiday travel behavior analysis of individual and subgroup using smart card transactions
Inference of travel behavioral attributes	Alsger et al.[3]	Proposing a model calibrated and validated to infer individual trip purpose of a PT user using smart card information	Smart card data, HTS[a], land use database, SEQSTM[b], GTFS, O-D survey data	Promising results obtained, shows a strong capability of the proposed model to predict trip purpose at a high level of accuracy
	Amaya et al.[4]	Estimating the residence zone of card users to enable socioeconomic variable for travel pattern analysis	Smart card data and OD survey data	The proposed method applicable for a segregate society allows to infer residence of the cardholders who are frequent PT users showing over 70% correct estimation
	Wang et al.[68]	Modeling location choice of metro commuters for after-work activities using smart card data	Smart card data	The proposed model performs well in explaining the station choices for after-work activities
	Goulet-Langlois et al.[29]	Proposing a methodology to identify clusters of PT users with similar activity sequence using smart card data	Smart card data and Socio-demographic information	Smart card data can be used to identify the connections existed between the demographic attributes of users and activity patterns identified exclusively from fare transactions

Table 1: continued

	Article	Focus	Data used	Key findings
	Han and Sohn[32]	Proposing a method to infer the sequences of activity using smart card information	Smart card data and land use information	Proposed continuous hidden Markov model (CHMM) is able to predict activity patterns which are consistent with the actual activity pattern
	Long et al.[46]	Understanding extreme PT riders using smart card data	Smart card data and household travel survey data	Smart card data along with household survey data can be used to identify the spatio-temporal patterns of extreme transit behaviors
	Arana et al.[7]	Determining the influence of meteorological conditions on transit ridership using smart card data	Smart card and AVL data	Smart card data can be used to determine the influence of external factor on PT ridership
	Kusakabe and Asakura[40]	Developing a data fusion methodology to estimate behavioral attributes of trips using smart card data to observe continuous long-term changes in the attributes of trip	Smart card data and person trip survey data	Smart card data can successfully estimate (86.2 %) the trip purpose using the proposed naïve Bayes probabilistic model which has low calculation load
	Lee and Hickman[42]	Inferring trip purpose and activity information of transit users using smart card transaction data	Smart card data, land use, GTFS[c]	Inferences can be made through the trip purpose assignment process using a typical weekday smart card data integrated with land use data
	Tao et al.[63]	Examining spatio-temporal dynamics or BRT trips in comparison with non-BRT trips using smart card data	Smart card data	Smart card data has the potentiality to reflect spatial heterogeneity in BRT/non-BRT trips
	Ma et al.[49]	Proposing data-mining procedures that models the travel patterns of transit riders using smart card data	Smart card data	Using data mining techniques, smart card data can be used to understand individual travel pattern and travel regularity
	Morency et al.[51]	Measuring the spatial and temporal variability of PT network use using smart card	Smart card data	Proposed data-mining techniques successfully provides continuous profile of spatial and temporal variability of transit use

[a] Household travel surveys (HTS)
[b] South East Queensland Strategic Transport Model (SEQSTM)
[c] Google's general transit feed specification (GTFS) is an open format updated by hundreds of transit agencies in the USA and used by Google to incorporate transit information

Table 2: Review of studies on big data for PT modeling. Source: prepared by the author, 2019.

	Article	Focus	Data used	Key findings
O–D estimation	Kumar et al.[39]	Inferring the trajectory of PT user using trip-chaining method, deriving information from smart card data	Smart card data and GTFS data	Proposed trip-chaining algorithm tries to relax the assumptions on the parameters such as GPS inaccuracy buffer zone for boarding stop inference for origin and destination inference
	Tamblay et al.[62]	Inferring the zonal O–D matrix for observed trip between two PT stops (i.e., bus stops or metro stations)	Smart card data, socioeconomic, land use, and network information	Smart card data can be used with other data to infer zonal O–D matrix and the proposed model captures the expected effect of land use on trip generation and trip distribution
	Gordon et al.[28]	Proposing a method to infer origins and destination matrices for bus passenger	Smart card data, AVL and survey data	Smart card data is a useful source to infer boarding and alighting times and locations for individual bus passengers, transfers between passenger trips of various public modes, and origin–destination matrices of linked intermodal transit journeys
	Munizaga and Palma[54]	Proposing a method suitable for large multimodal PT system to predict origin–destination (OD) matrix obtained from entry-only smartcard data	Smart card data, AVL data and geo-coded PT network	Linked journey O–D matrix can be constructed for a multimodal PT system using interchange inference algorithm using smart card data
	Wang et al.[67]	Inferring O–D for bus passenger using data from automated data collection systems (ADCS)	Smart card data, AVL and manual survey data	It is feasible and easy to apply trip-chaining to infer O–D for both weekend and weekday and alighting stop of bus passenger, using smart card data
	Barry et al.[9]	Proposing a method to determine O–D trip tables by using entry-only smart card data for all PT user (subway, local and express buses, ferry, and tramway)	Smart card data	O–D matrix can be developed using smart card data for multimodal transport network even when AVL data is not available
	Chu and Chapleau[20]	Derive more complete information from smart card for planning purposes	Smart card data	Smart card can be used to infer passenger journeys, analyze transfer activity and synthesize vehicle load profile for the better analysis of linked trips, trip chains, and activity space using run time estimation
	Trépanier et al.[65]	Estimating trip destination using smart card fare collection data	Smart card data	Smart card data can be used for destination inference of bus passenger when alighting information is not available

Table 2: continued

	Article	Focus	Data used	Key findings
	Zhao et al.[76]	Proposing a method for predicting rail passenger O–D table from smart card data	Smart card data and AVL data	Smart card data can be used to infer O–D matrix (rail to rail and rail to bus) for rail passenger from an origin-only smart card data to replace expensive passenger O–D surveys.
	Barry et al.[10]	Proposing a method to determine station-to-station O–D trip tables by using entry-only smart card data for subway user (unimodal trip)	Smart card data, Travel diary survey data for validation purpose	Proposed destination inference model using metro card information can be used to create O–D matrix for different temporal scales
	Farzin[25]	Creating O–D matrix using multiple data source along with smart card data	Smart card data and AVL data	Multiple data can be infused with smart card data to develop and validate zonally aggregated O–D matrix
Route choice modeling	Cheon et al.[19]	Developing a method for analyzing the route choice of travelers in multimodal transit networks by considering multiple attributes	Smart card data	The developed model considers coexistence of various mode in a single network including multiple attributes to effectively reduce the unreasonable paths with high accuracy
	Nassir et al.[56]	Proposing a path choice model using smart card	Smart card data	Proposed recursive link-based choice model allows model calibration with incomplete path choice observations with transit smart card data in higher-frequency bus and rail services
	Jánošíková et al.[35]	Estimating route choice model for urban PT using smart card data	Smart card data, street map and time table	In-vehicle travel time, transfer walking time and to get from alighting stop to trip destination, the need to change, and the time headway of the first transportation line, can be determined by the combination of smart card data with other data sources

Table 3: Review of studies on big data in PT performance improvement. Source: prepared by the author, 2019.

	References	Aim		Major observation
Measurement of performance assessment indicators	Lee et al.[43]	Measuring the accessibility to PT using mobile phone data	CDR data and census data	Proposed Huff model-based floating catchment area method measures reliable time-varying accessibility to PT using mobile phone data
	Tavassoli et al.[64]	Modeling passenger waiting time at transit stop using smart card data	Smart card data and GTFS data	Log-logistic AFT models is inferred to be the best fit for passenger waiting time using smart card data
	Tu et al.[66]	Analyzing the spatial variations of urban PT ridership using smart card data	Smart card data and GPS trajectories	The effects of demographic, land use and transportation factors on the ridership of PT can be explored using GWR analysis using smart card data
	Zhou et al.[79]	Developing a model to calculate bus arrival time using smart card data	Smart card and travel survey data	Bus arrival time is calculated using the distribution of the card swiping time distribution, occupancy and the seating capacity information
	Zhu et al.[80]	Proposing a model to infer left behind passenger using smart card data	Smart card and AVL data	The estimated probabilities of passengers being left behind using smart card data is similar to manual survey results and provide crowding information
	Hong et al.[33]	Estimating both the physical and schedule-based connections of metro passengers by examining the Smart Card data	Smart card data	Promising results obtained and the model estimated precisely the passengers boarding, transferring, and alighting of trains based on the entry and exit times and stations of a passenger
	Min et al.[50]	Proposing method to recover the arrival times of trains from the gate times of metro passengers from smart card data	Smart card data	The proposed method is applicable, when logs are missing for an entire line and the procedure recovered the arrival time of higher accuracy
	Aguiléra et al.[1]	Measuring quality of service and passenger flows using mobile phone data	GSM, smart card data and field observation data	Train occupancy levels, travel times, and origin–destination flows is estimated at a very fine-grain level using GSM data and compared with the field observations (train trajectory) and smart card data

Table 3: continued

	References	Aim		Major observation
Evaluation of performance	Liu et al.[44]	Proposing method to replicate the multi-modal PT system	Smart card data	The disaggregated replication provides trip information with precision of a few minutes and the outputs are precise temporal and spatial travel demand analysis, transfer pattern analysis, traffic condition investigation and bus utilization analysis
	Liu et al.[45]	Assessing the impact of fare policy change on ridership using smart card information	Smart card data	Impact of fare policy on PT ridership can be assessed through the comparison of number of card users, their journeys, and travel costs before and after the policy reform
	Zhou et al.[78]	Explicating the potentiality of big data in quantifying and visualizing the relationship between transit fare, space and justice	Smart card data	Proposed and implemented methods such as "trajectory rebuilding", "fare matching", "segment tagging", "desired line/stop visualization", "commuter identification" and "scenario analysis" using smart card data
	Moyano et al.[52]	Evaluating the importance of access and egress times to/from HSR stations in an urban context	GTFS, speed profile and Twitter data	Travel time measures are analyzed temporally and spatially for access/egress to/from stations considering both taxis and PT
	Yap et al.[72]	Improve the prediction accuracy of the impact of planned, temporary disturbances on PT usage	Smart card data	Proposed rule-based three-step search procedure results in higher accuracy in predicting PT usage during disturbances
	Pereira et al.[58]	Predicting PT arrivals under special events using Internet	Internet	Proposed a methodology extracts events information from the Internet and matches such information with bus and subway tap-in/tap-out data
	Williams et al.[70]	Collecting a comprehensive data set on a semi-formal transit system using cell phones	Cell phone data	The proposed method shows how to transform cell phone data into a GTFS format useful for planning, research, operations, and transit routing applications
	Ma and Wang[48]	Developing a data-driven platform for online PT performance assessment	Smart card data, AVL data and geospatial data	The proposed framework demonstrates several transit performance indicators at different scales (e.g., network level, route level, and stop level) and the feasibility of establishing a web-based e-science system for transit performance measures

Appendix B: Additional information of pilot

Given the limited resources in this project, we could not execute a full fletch pilot that involve new data-collection and new/advanced statistical analysis. What was deemed feasible where pilots that are based on

A. extending earlier approaches and analysis with previously processed data (see suggestion 1 below)
B. outlining new data collections and analysing methods; i.e. planning rather than executing (see suggestion 2 below)
C. new data analysis and/or new data sources (not earlier used) in case synergies with other ongoing project at TØI can be made (see suggestions 3 and 4 below)

More concretely the following four suggestions for pilots were made:

1. Reproducing the Varela et al statistical approach of inferring VTTS based on survey data and transport model data. The main idea is reduce the measurement error in time and cost attributes from the network models by employing latent variable models.
2. Outlining a pilot (and possible main project) to use the Fotefar GPS-tracking app (potentially with supplementing surveys) to study mode and route choice behaviour and estimate valuation for various travel modes and unit values.
3. Using aggregated mobile data from 3 routes between Oslo (Sandvika) and Hemsedal to derive absolute VTT for car drivers and (possibly) comfort differences (VTTS multipliers for different infrastructure). The main idea is to showcase that aggregated mobile data can be used as an (improved) alternative for counting data in studying route choice behaviour between “parallel” motorways.
4. Calibrating the VTTS for car drivers within a MATSim model for Oslo/Akershus against (hourly) traffic count data.

The clients choose pilot suggestion nr 3, which is described in the section 5.

Appendix C: Derivation of equation 3

$$G_2 = c * D_2 + B_2 + \omega * T_2$$
$$G_3 = c * D_3 + B_3 + \omega * T_3$$

$$P_2 = \frac{e^{\mu * G_2}}{e^{\mu * G_2} + e^{\mu * G_3}} = \frac{1}{e^{\mu * (G_3 - G_2)} + 1}$$
$$P_3 = \frac{e^{\mu * G_3}}{e^{\mu * G_2} + e^{\mu * G_3}} = \frac{1}{e^{\mu * (G_2 - G_3)} + 1}$$

$$G_3 - G_2 = \omega\,(T_3 - T_2) + \;(B_3 - B_2) + c(D_3 - D_2)$$

$$P_2 = \frac{1}{e^{\mu * (\omega\,(T_3 - T_2) + \,(B_3 - B_2) + c(D_3 - D_2))} + 1}$$

$$P_3 = 1 - P_2 = 1 - \frac{1}{e^{\mu * (\omega\,(T_3 - T_2) + \,(B_3 - B_2) + c(D_3 - D_2))} + 1}$$

Definerer

$$T_3 - T_2 = X$$
$$(B_3 - B_2) + c(D_3 - D_2) = Y$$

System of 1equations and 2 unkowns (μ and ω)

$$P_2 = \frac{1}{e^{(\mu * (\omega * X + Y))} + 1}$$

Solve for μ

$$(e^{(\mu * \omega * X + \mu\, Y)}) = \frac{1}{P_2} - 1$$

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$$\mu * (\omega * X + Y) = \ln\left(\frac{1 - P_2}{P_2}\right)$$

$$\mu = \ln\left(\frac{1 - P_2}{P_2}\right) * \frac{1}{\omega * X + Y}$$

Alternatively, solve for ω

$$\mu * (\omega * X + Y) = \ln\left(\frac{1 - P_2}{P_2}\right)$$

$$\mu * (\omega * X) = \ln\left(\frac{1 - P_2}{P_2}\right) - \mu Y$$

$$\omega = \frac{\ln\left(\frac{1 - P_2}{P_2}\right) - \mu * Y}{\mu * X}$$

Inserting Y and X give the equation 3) in the main text.

Appendix D: Score cards for section 3.6.5

Data source	MaaS ordereing data	Mobile data	Tracking data from commerical providers
Unit value	**VTTS PT short**	**VTTS PT long distance**	**VTTS PT long distance**
Access to relevant and updated RP data	2	3	2
Resources required for data access and maintenance	3	2	2
Resources required for data processing	4	3	4
Data volume	4	2	2
Coverage (national)	3	3	4
Representativity	3	4	3
Observation of actual choices	5	4	4
Quantification of attributes and costs of chosen alternative	4	3	4
Identification/modelling of non-chosen alternatives (choice set)	5	2	4
Quantification of attributes and costs of non-chosen alternative	4	3	4
Variation and correlation i central attributes	2	2	2
Possibility to control for other effects	3	1	2
Possibility to segment (current segmentation)	2	1	1
Possibility for combined RP-SP models and other advanced estimation methods	3	1	2
Possibility to frequent and continuous data collections in future	4	5	5
Possibility to segment results beyond current segmentation	3	2	3
Synergies with transport models	3	3	3
Other synergies	3	3	2
Relevance for new trends/technologies	4	2	3

Appendix E: Score cards for section 3.7

	App panel with GPS-tracking				dedicated cameras and sensors			Toll transaction data	Tracking data from commerical providers
	VTTS W/C	Car reliability	Raod congestion	Insecurity of avalances	Car time variabiliy	Road congestion	Insecurity of avalances	Road congestion	Road congestion
Access to relevant and updated RP data	4	4	4	4	2	2	2	3	3
Resources required for data access and maintenance	3	3	3	3	2	2	2	3	3
Resources required for data processing	4	4	4	4	3	3	3	4	4
Data volume	3	4	4	3	3	3	2	3	3
Coverage (national)	3	3	3	3	3	3	3	4	4
Representa-tivity	3	3	3	3	4	4	4	2	2
Observation of actual choices	4	5	5	5	4	4	4	4	4
Quantification of attributes and costs of chosen alternative	4	4	4	4	3	3	3	3	3
Identification/modelling of non-chosen alternatives (choice set)	3	3	3	3	3	3	3	3	3
Quantification of attributes and costs of non-chosen alternative	3	4	4	4	3	3	3	3	3
Variation and correlation i central attributes	4	4	4	4	2	2	2	2	2
Possibility to control for other effects	4	2	4	4	2	2	2	1	1
Possibility to segment (current segmentation)	3	3	3	3	4	4	3	3	3
Possibility for combined RP-SP models and other advanced estimation methods	4	4	4	4	2	2	2	2	2
Possibility to frequent and continuous data collections in future	5	5	5	5	3	3	3	5	5

Possibility to segment results beyond current segmentation	3	3	3	3	4	4	4	3	3
Synergies with transport models	4	4	4	4	3	3	3	3	3
Other synergies	4	4	4	4	3	3	3	2	2
Relevance for new trends/ technologies	5	5	5	5	4	4	4	3	3

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