Improving Data-Driven Decision-Making in Public Transport

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Preface

This master’s thesis is a result of a study conducted in the subject IS-501, Master thesis in information systems, at the University of Agder, spring 2021. The study is conducted by Marius Friberg Vika and Jørgen Mosvold Salvesen as a final study in their master's degree in Information Systems at the University of Agder. The background of the study is the increasing need for data-driven decisions in public transport sector, where the study aims to overview and propose improvements.

First and foremost, we would like to thank Red Rock and our contact, CSCO Lars Lohne, for introducing us to the subject. Thank you for providing us with valuable information and contacts from the public transport sector.
We would like to thank all the informants involved in the study. Thank you for benevolently answering questions related to the study and for facilitating interviews in your organisations in a good way.
Furthermore, we thank our supervisors, Professor Dag Håkon Olsen and Professor Eli Hustad, at the University of Agder for good guidance, good conversations, and useful inputs along the entire research process.
Finally, we would like to thank our families for providing us with support and encouragement along the way.

Kristiansand, 03.06.2021.

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Abstract

This master thesis focuses on data-driven decision-making in Norwegian public transport, aiming to identify and categorise different types of decisions and related data sources. Furthermore, the study evaluates current capabilities among the actors studied for creating efficient decision-making processes and develops a framework that proposes improvements. The overall research question is “How can data-driven decisions be improved in public transport?”.

Due to the rapid changes and evolution of the business world, organisations need to constantly adapt and make frequent decisions aligned with their goals and objectives. Therefore, the ability to analyse data provided by information and communication technologies and apply this as information in decision-making processes is crucial for organisations, including the public transport sector. The public transport sector has existed for several decades, thus being affected by several intuition-based decision-making processes.

We started our study with a systematic literature review to get an overview of the research subject. We thereafter conducted a case study involving different actors from the Norwegian public transport area. Ten semi-structured interviews were performed in public transport organisations that operate buses or ferries. The informants were decision-makers at different levels of the organisations. With this selection of informants, we gained insights on decisions and capabilities viewed from different perspectives.

The results indicate several types of decisions and data sources supporting them, and the decisions were divided into operational, tactical, and strategic decisions. Furthermore, the results show that challenges such as culture, knowledge, and maturity limit the data-driven decision-making processes.

The results suggest that to improve data-driven decisions in public transport, the sector’s capabilities need further development:

1. Making the infrastructure support the assembling of high-quality data.
2. Making the analytic capacity support the analysis to ensure that the resulting data is relevant.
3. Developing the culture to support the use of relevant data to inform decisions.

We suggest that these three steps will result in an improved data-driven decision-making capability. Furthermore, the results suggest contextual data as an additional data source to provide causality to analysis, and to support the standardisation of analytics.

The study is limited to public transport organisations operating buses and ferries. Further research should gather quantitative data on capabilities to provide more generalisable results. Moreover, the study forms a basis for a longitudinal case study to better overview culture, maturity, architecture, and their development over time. This study has implications for future research regarding the practical use of contextual data in public transport. Further research should also take into consideration the differences between public and private sector.

Table of Contents

List of figures

List of tables

1 Introduction

This thesis is set out to study how data-driven decisions in public transport can be improved. This section will explain the background for this thesis, our motivation, target group, and outline for the rest of the thesis.

1.1 Background for research

In this thesis, we are exploring data-driven decisions and their potential concerning public transport. The research area we are focusing on is public transport in Norway. The overall problem definition for this research project is:

“How can data-driven decisions be improved in public transport?”

To address this research question, we used a qualitative approach. The problem we are addressing is that further research is needed to improve data-driven decision-making in public transport. For us to uncover improvement potential for data-driven decisions in public transport, we first need to know how the decisions currently work; therefore, we need to answer some underlying research questions:

"How are decisions made in public transport, and what sources of data are applied?"

"What are the challenges for data-driven decisions in public transport?"

Today's business world is quite turbulent with frequent changes and adaptation needs, thus creating a need to make frequent decisions that are correct and correspond to the organisation's goals. There is a vast amount of data available that companies are focused on exploiting for competitive advantages. The vast amounts of data have outstripped the capacity of manual analysis, and to some extent, exceeded the capacity of conventional databases; therefore, well-thought processes and infrastructures to collect and analyse data are critical to succeed (Provost & Fawcett, 2013). It is acknowledged that big data plays a significant role in effective decision-making (H. Chen, Chiang, & Storey, 2012; Davenport, 2013; Waller & Fawcett, 2013); this applies to all branches of human activity, including public transport (Sobková, Certicky, & Jiracek, 2019).
The service demand of passengers and new management requirements are increasing, thus making the evaluation of urban bus service more and more critical (Shi et al., 2021). The rise of smart cities concepts also sees the data-driven transport policy as one of the key pillars (Urbanek, 2019).
The thesis is aimed towards public transport. The data collection took place in organisations operating buses or ferries; hence our focus is such public transport organisations, emphasising organisations operating buses.

1.2 Motivation for the study

Motivation for this study can be seen from several aspects. The Norwegian government has set goals and ambitions to take advantage and utilise the opportunities inherent in data for increased value creation, new jobs, and a more efficient and sustainable public transport sector. Better utilisation of data is essential if Norway wants to transition to a more sustainable society and a greener economy. (Det kongelige kommunal- og moderniseringsdepartementet, 2020).

The improvement of the service level of bus systems is an urgent need for the healthy development of urban traffic (Shi et al., 2021). We were first introduced to the increasing need for data-driven decisions in public transport by a local firm developing digital solutions for public transport enterprises. This firm pitched the initial idea of this thesis by introducing us to the emerging need for better decisions in public transport. This firm gave us an initial look into their digital platform for managing tickets, sales, routes, and vehicles, while also explaining the future potential for such platforms.

While big data and data-driven decision-making have a growing body of research, there is a lack of general standards in the processes of public transport, thus creating a need for further research.

1.3 Target group

This master thesis has two primary audiences. First, the public transport sector, and secondly, the businesses developing digital platforms and solutions for public transport. We show that the framework is an essential contribution to developing new and existing solutions, both for internal and external contributors to decision-making.

The master thesis should also generally provide valuable input to individuals and organisations interested in data-driven decisions.

1.4 Thesis outline

The following chapters are structured as follows:

- Chapter two is the theoretical foundation, presenting previous research in relevant fields.
- Chapter three describes our method in conducting this study.
- Chapter four describes the context of the study.
- Chapter five presents the results from both the interviews and analysis of public reports.
- Chapter six discusses the findings in combination with literature.
- Chapter seven concludes the thesis.
- In chapter eight and nine, you can find references and appendix.

2 Literature

As a basis for this thesis, we will summarise previous research on data-driven decision-making and linked aspects to create a clearer picture of the subject. The literature findings will contribute to making our findings more comparable with other research (Creswell, 2011). The research area has many published articles; therefore, it is appropriate for us to ensure that the literature basis has a good quality in the form of trustworthy research.

The literature gathering is in the form of a systematic literature review. This method is great for obtaining, understanding, and coping with all the information and literature that is available involving our subject. Otherwise, it would be challenging to understand what data-driven decisions and their linked aspects include if we have not systematically researched the subject and categorised the different aspects of it. Our approach aims to follow the fundamental principles behind systematic literature review (Pittway, 2008). The literature review is transparent; the approach is recorded and available during and after our initial study. Our approach includes a series of precise steps on how we have collected literature to make our literature review as straightforward as possible.

Before identifying which articles to research, we set up a set of criteria for picking articles:

1. The title should be relevant: It should at least consist of one of our key terms (E.g., “Data-driven decision” or “decision-making” or “big data” or “public transport”)
2. The subject must consist of great relevance: It needs to consist of aspects from the key terms, and preferably about decision-making processes.
3. The articles must be trustworthy: E.g., published in a journal, written by recognised authors, contain reliable references.
4. Articles should be published in or after 2010; this is because data-driven decision-making is ever-changing processes, where older articles might not apply to current practices.

The database we have used to identify articles is Scopus. This database is available to us as students through The University of Agder. We chose this database as it is easy to use, both for fast and advanced searches. This database is trustworthy, which helps us find articles meeting our set of criteria.

As a systematic approach to study previous research, we based the searches around the search words “decisions” and “decision making”. After that, we combined these with search words such as “data-driven”, “public transport”, “big data”, “knowledge management”, “Strategic decision-making”, “business analytics”, “data analytics”, “organisational performance”, and “enterprise architecture”.

Table 1 shows a list of the different search strings used in the literature review.

Table 1 - List of search strings

Search #	Search string	Hits
1	TITLE-ABS-KEY (public AND transport) AND TITLE-ABS-KEY (data AND driven AND decisions) AND TITLE-ABS-KEY (big AND data)	11
2	TITLE-ABS-KEY ("public transport" AND "decision-making")	999
3	TITLE-ABS-KEY ("public transport" AND "data-driven decision-making")	2
4	TITLE-ABS-KEY ("public transport" AND "big data" AND decision)	42
5	Title contains “Knowledge management” AND subject contains “Strategic decision making” NOT all fields “Data analytics”	50
6	(Various conferences) AND TITLE-ABS-KEY ("knowledge management" AND "strategic decision making" OR "business analytics" OR "data-driven decision making" OR "data analytics") 2010 - present	42
7	(Various conferences) AND TITLE-ABS-KEY ("strategic decision making" OR "business analytics" OR "data-driven decision making" OR "data analytics" OR "big data" OR "organizational performance" AND "Enterprise architecture") 2010 - present	25
8	TITLE-ABSTRACT-KEYWORDS “organizational performance” AND “decision making” AND “data analytics” 2010 - present	13

From table 1, we see that many of the searches contain a relatively small amount of hits. Before starting the search process, we used Google Scholar to overview the research field, thus leaving further searches narrow and specified to ensure quality hits. Articles were in the first round picked based on the relevance of their titles and abstracts.
In addition to articles identified through Scopus, we also used several websites and books and supplemented them with articles found through references.

2.3 Literature findings

This section will present different findings from the selected articles to provide a thorough overview of previous research.

2.3.1 Different types of decisions

Early on in this study, we identified in our findings that there are four types of decisions (Intezari & Gressel, 2017). (1) Structured Decisions based on Structured Data (SD-SD) are decisions made by an organisation that follows structured processes and pre-defined procedures to make strategic decisions based on unstructured data. (2) Structured Decisions based on Unstructured Data (SD-UD). These decisions are based on “weak signals” from, e.g., social media or other sources that contain powerful insights (Harrysson, Métayer, &

Sarrazin, 2014). These types of decisions are made based on unstructured data but through pre-defined procedures. (3) Unstructured Decisions based on Structured Data (UD-SD). This decision approach has decision-making as an unstructured process that suggests that decision-making steps do not necessarily follow a set order of tasks, but that unstructured decisions rely more on human judgment, experience, prior knowledge and interpretation of the decision context and alternatives. (4) Unstructured Decisions based on Unstructured Data (UD-UD) are decisions based more upon intuition and feelings instead of procedures and structured data. An example to show where UD-UD might be applied is when an organisation is trying to incorporate data from social media into strategic decisions. This can be a challenging task and might result in intuition-based decisions instead of data-based decisions. Intuition-based decisions are not necessarily bad decisions; it really matters what intuition is based on. Our findings show that KM practices have a positive direct impact on rationality and planning effectiveness. In addition, knowledge management practices provide a solid contribution to intuition (Giampaoli, Aureli, & Ciambotti, 2019).

It is interesting to see the different decision-making processes that exist. By defining these, it is easier to be aware of the different decision-making contexts when trying to answer our research question. For this study, we decided further to categorise different decisions into different levels of decisions. An organisation must make decisions that affect the entire business enterprise. Some of these may have short-term implications, while others have long-term implications. There are three main categories of decisions: strategic, tactical, and operational (Chand, n.d.).

Operational decisions are the day-to-day decisions that only have a short-term impact on an organisation. Examples of operational decisions can be (but are not limited to) scheduling employees, training, purchasing, assigning work, selling, and more. Operational decisions do not have long-term impacts on the organisation alone, although they guide the implementation of strategic and tactical plans. *Tactical decisions* concern decisions that support the organisation's overall strategy. Examples of this can be evaluation, the launch of new products or services, change of products, and more. Strategic decisions have a long-term impact on an organisation. *Strategic decisions* decide on an organisation's goals and objectives and involve the strategies to achieve these.

2.3.2 Culture and Knowledge Management

The generic definition of *knowledge management* is "the processes of creating, sharing, using, and managing the knowledge and information of an organisation" (Intezari & Gressel, 2017). Throughout the different articles, several other aspects are linked to KM. "KM practices have a mediating role in the application of big data analytics and organisational performance" (Shabbir & Gardezi, 2020). It is a clear finding that if an organisation has built up good KM practices, their application of other related aspects, such as big data and data analytics, could significantly improve the organisational performance, which in return will improve their competitive advantage. Superior KM performance has a statistically significant positive association with firm valuation, thus also making KM competencies a vital ingredient in a firm's performance from the standpoint of market-based valuation (Wu & Holsapple, 2013).

Based on these findings, we assume that both big data and data analytics are tools that need to be in place to achieve effective (superior) KM.

Chen (2010) states that progressive and enduring culture is believed to be a foundation for efficiency within organisations. Developing a good organisational culture is an essential aspect of being an agile and competitive organisation. If there is a good knowledge culture, employees are more likely to teach each other knowledge that would otherwise not be shared, which again provides employees more data to make better and revised decisions. Staadt (2015) found that organisational culture is the most critical enabler for enhancing knowledge sharing in projects; he suggests that organisations need to invest in appropriate infrastructure and capabilities to manage uncertainties. Culture enhances the stability of organisations and serves as a sense-making device that can guide and shape behaviour (Oyemomi, Liu, Neaga, Chen, & Nakpodia, 2019). These aspects directly relate to our research question. It is a significant capability for decisions because a good culture is an enabler for knowledge sharing, affecting better thought-through decisions.

Technological benefits of BDA are going to influence the future workplace and tasks; therefore, it necessitates social change within organisations (Roßmann, Canzaniello, von der Gracht, & Hartmann, 2018). Based on this, we see organisational culture, significantly 'knowledge culture', as the foundation for enhanced capabilities in data-driven decision-making.

2.3.3 Organisational performance

Organisational performance (OP) involves the organisation's performance against its objectives and goals (Richard, Devinney, Yip, & Johnson, 2009). Knowledge culture has a significant impact on organisational performance. "Knowledge sharing is crucial for attaining a competitive edge in organisations" (Oyemomi et al., 2019), where knowledge motivates innovation, thus increasing the OP. A regression analysis conducted on businesses in Kuwait (both public and private sector) shows a clear positive linear correlation between KM-processes and OP-indicators. In the same study, it is indicated that even though all KM processes are essential to OP, it is the ability to leverage knowledge and then convert it into action (decisions) that is the most effective KM process regarding OP (Dzenopoljac, Alasadi, Zaim, & Bontis, 2018).

Knowledge generation (KG) and knowledge flow (KF) promote firm performance within organisations. While there is no direct relationship between an organisation's performance and knowledge storage, we can assume that organisational learning mediates the relationship between KG, KF and performance (Obeso, Hernández-Linares, López-Fernández, & Serrano, 2020).

We also see that from the standpoint of achieving a robust financial performance, KM is a crucial factor to consider for organisations (Holsapple & Wu, 2011).

2.3.4 Big data analytics and application

Big data analytics (BDA) improves firm decision-making quality (Ghasemaghaei, 2019). In our findings, the role of knowledge sharing, and data analytics competency became clear. Ghasemaghaei (2019) conducted a study based on 133 US-based firms to understand the role of the mentioned terms. The study resulted in clear guidelines: (1) Data analytics improve knowledge sharing in organisations. (2) Knowledge sharing fully mediates data analytics usage impact on decision quality. (3) Knowledge sharing does not necessarily improve firm decision quality; its impact is heavily moderated by data analytics capability and competency. (4) Data analytics competency moderates knowledge sharing impact on decision quality. Organisations with low levels of data analytics-based capabilities and resources cannot improve their decision quality by applying data analytics tools. This proves that a high level of BDA capabilities is needed to improve decisions based on data.

This statement is also strengthened by Harrysson et al. (2014), where “weak signals” among big data is emphasised. “Weak signals” are often hidden amid the “noise”, ergo; useful data is often hard to find, thus making BDA capability essential to identify these “weak signals” and applying them for data-driven decisions.

BDA capability has a positive moderating effect; the more substantial the capability, the bigger the effect of big data has on the organisation (Hao, Zhang, & Song, 2019). Operational tasks and decisions are increasingly being automated because of data-driven approaches (Roßmann et al., 2018).

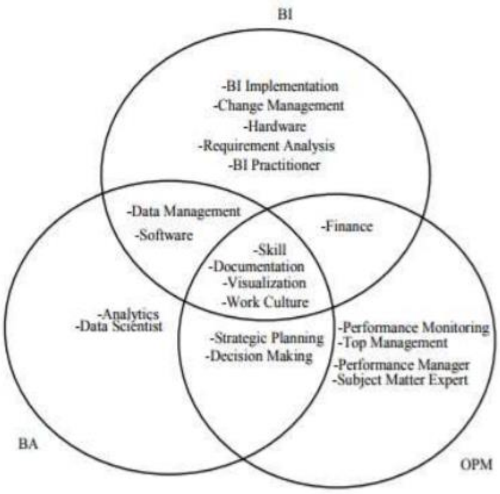

Figure 1 - The essential factors for successful OP (Abai et al., 2019, p. 178)

Several findings showcase the critical factors for implementing business intelligence, analytics, and organisational performance management. These three are like the literature we have identified in this paper - Skills, documentation, visualisation, and culture. These findings clearly state the “requirements”/capabilities needed for better decisions.

2.3.5 Data-driven decisions in public transport

“With the increasing service demand of passengers and new management requirements, the evaluation of urban bus service is becoming more and more important” (Shi et al., 2021). Shi et al. (2021) also states that the service-level improvement of bus systems is an urgent need for the healthy development of urban traffic. The capability to analyse big data provided by information and communication technologies and the capability to use and apply this information in the decision-making process are crucial elements to increase competitiveness

and effectiveness in all sectors, particularly the transport sector. “The data-driven transport policy is also one of the key pillars of a smart city concept” (Urbanek, 2019).
Present societal and governmental trends, emerging technologies, and new tech-enabled transport businesses suggest that the current system can change dramatically. As we continue to invest heavily in public transport infrastructure, big data analytics can further monitor the medium-and long-term performance outcomes and make better-revised decisions. (Lock, Bednarz, & Pettit, 2021).

2.3.6 Application of data in public transport

There are several sources of data available in public transport to take advantage of to make better decisions. Shi et al. (2021) mentions some of them. The bus location data records data such as bus route number, vehicle number, longitude and latitude coordinates, instantaneous speed, and other information. By analysing this data, the information of bus operation time, arrival time, speed, and distance between stations can be recorded.
The travel chain data records each travel stage of travellers; date, card number, travel stage, travel time, travel distance, transfer information, transfer time, start time, end time, and more. By analysing the travel chain, travel time-related information can be obtained.
Shi et al. (2021) also mentions bus static attribute data, which covers route name, direction, station serial number, station name, longitude and latitude, station ID, and more. This is the basis of bus multi-source data association.
Lock et al.’s (2020) case study in Australia highlights the possibilities of big data gathering and utilisation in the public transport business. They were using the data to build heat maps to see real-time transport performance data. This data can help users identify which routes have relative lower/higher values than others. Users can also observe patterns; are things getting worse or better, which is an effective tool when making decisions. Other use cases can also be developed for specific users (Lock et al., 2021).

2.3.7 Maturity and capabilities

The literature has made clear that capabilities serve a central role in data-driven decision-making. “IT architecture is often assumed to follow business strategy, to align IT with the business’s strategic objectives. Increasingly, though, many business strategies depend on specific underlying IT capabilities” (Ross, 2003). A successful IT architecture is the organising principle for various technologies that are used to support business processes. It is typically composed of various policies and procedures that enable the organisation to make informed decisions regarding these technologies. The enterprise architecture refers to the various capabilities that an organisation must enable its business goals. It also includes the ability to access and integrate various data sources for new applications. It is also able to replicate systems in different locations. Instead of developing a list of possible technology capabilities, a well-designed enterprise IT architecture focuses on the various elements that are most critical for a firm’s strategic objectives. IT architecture competency is a firm’s ability to create a reinforcing pattern of tightly aligned business strategy and IT capabilities. Ross (2003) developed the four IT architecture stages: (1) An application silo architecture consists of architectures of individual applications rather than a unifying architecture for the entire enterprise. (2) A standardised technology architecture is where IT becomes enterprise-wide and provides efficiencies through the standardisation of technology. (3) a rationalised data architecture expands to include standardisation of data and processes. (4) A modular architecture supports loosely coupled applications and data that can be used globally while enabling local differences. Figure 2 shows the changing resource allocations across architecture stages as an organisation matures from the application silo architecture stage to the modular architecture stage.

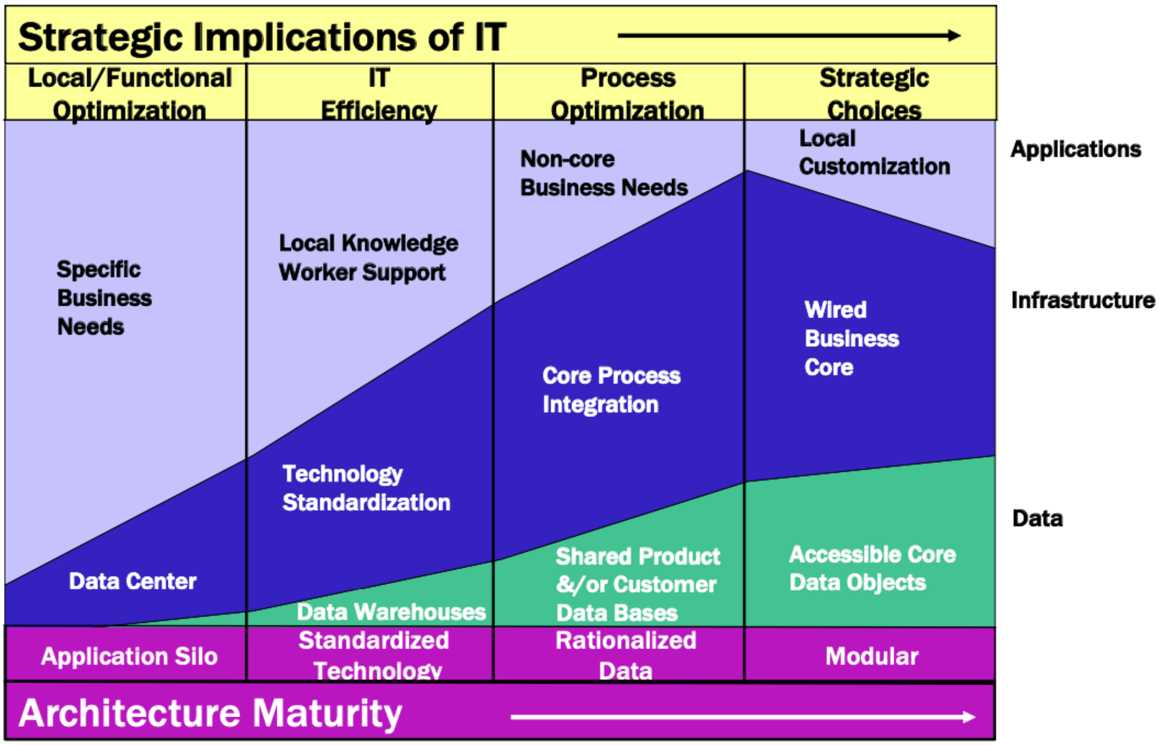

Figure 2 - Changing resource allocations across architecture stages (Ross, 2003)

This model can help us in understanding the organisations we interview in this thesis on a higher level.

2.3.8 Data-driven decision-making capabilities

During our literature review, we identified an article suggesting how data-driven decision-making capabilities can be improved in education. Gill et al. (2014) presented a theory of action for data-driven decision-making in education in three steps to achieve the goal of improving the capabilities of DDDM:

1. Assemble high-quality raw data: This step includes determining the sources from where to gather data and how to gather it.
2. Conduct analysis that ensures resulting data is relevant and diagnostic: If data serves the decision-making goal, they must be relevant to the decision-maker and appropriately diagnostic for the decision itself.
3. Use relevant and diagnostic data to inform instructional and operational decisions: “Even the best data and the best analysis will not improve outcomes if the results are not used” (Gill et al., 2014). A culture that facilitates data usage is necessary to ensure that data is not ‘thrown away'.

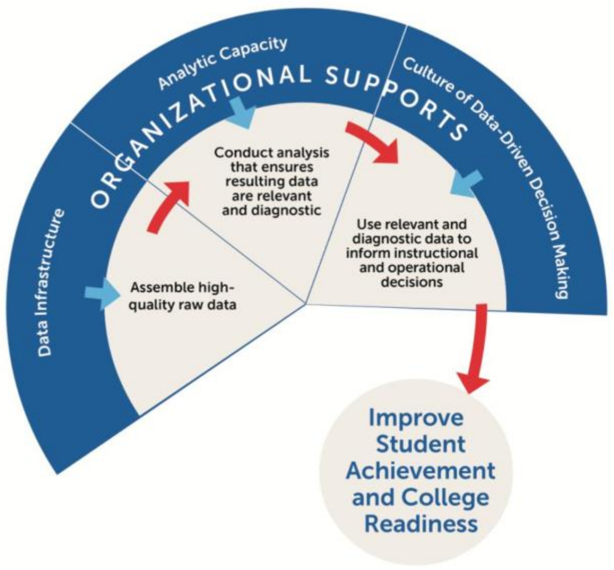

Figure 3 - Data-driven decision-making in education (Gill., et al. 2014)

We found the article to provide great input on DDDM capabilities. The article is aimed towards education; thus, capabilities are applicable across several sectors.

2.4 Summary of literature review

In the literature review, we have identified several aspects. Decisions vary in forms, where the decision and data might be both structured and unstructured. The form of the decision varies depending on the decision itself. There is not always a straightforward solution to how the decision should be processed. However, culture plays a significant role in how decisions are made, thus becoming a significant capability for improved decision-making processes. Knowledge management practices determine where and how data is gathered, applied, and distributed. This implies that good knowledge management practices need to be in place to facilitate improved decision-making processes. An organisation's culture and KM practices directly affect organisational performance, implying the importance of culture and KM for decision-making.

Big data analytics (BDA) and gathering improve the decision-making quality of organisations, but the capability and competency of BDA are moderating the quality of the decision-making processes. Organisations with low levels of data analytics-based capabilities and resources cannot improve their decision quality by applying data analytics tools. A high level of BDA capabilities is needed to improve decisions based on data.

The improvement of public transport systems is crucial for the healthy development of urban traffic. There are several sources of data to take advantage of that can improve several aspects of the public transport sector, both internally by improving the organisational performance and externally by meeting demands set by government institutions.

This systematic literature review has given us a better understanding of how decisions work and how data can be gathered and applied to them. We have also gained significant insights into the crucial capabilities and competencies needed to achieve data-driven decision-making. The review has also given us insights into the importance of public transport systems' development and how different data sources can be applied to support decisions.

3 Method

This study is set out to determine how data-driven decision-making can be improved in public transport. Our research is based on the philosophical assumption of interpretivism, which is an assumption that tries to identify, explore, and explain how the factors in a setting are related and interdependent. The aim is to create a rich understanding of a context (Oates, 2006). In this chapter, we will describe our research strategy and the methods that are applied. Furthermore, we will present the different criteria for the chosen method, describe how we collected the data, and analyse it. Lastly, we will explain how ethical issues are addressed.

3.1 Qualitative approach

To solve our problem, we chose a qualitative approach. The public transport sector in Norway has many different actors, so we find it more fitting to apply a qualitative approach to get as detailed information as possible. The qualitative approach we applied was a case study. A case study aims to gather empirical data and investigate a phenomenon within its real-life context (Oates, 2006). The phenomenon we are investigating is decision-making processes in public transport and their relation to data. To investigate this, we applied a descriptive case study to provide us with a rich and detailed analysis of decision-making processes in public transport. Our method to carry out the descriptive case study was in the form of semi-structured interviews with several actors from Norwegian public transport sector. We wanted to identify the current situation, so the descriptive case study was applied to a short-term, contemporary study examining what is happening in the current case (Oates, 2006).

3.2 Selection of informants

Because this is a qualitative case study, we wanted to study a selection of organisations and relevant roles. Therefore, it was appropriate to base this study on a non-probability sample of the discretionary selection type. This means that the researchers select the informants after assessing their relevance to the study (Oates, 2006). In our case, this assessment was made based on potential informant organisations' relevance and the informant's role.
The study is based on ten interviews in six different organisations where the roles directly correlated with data and decision-making. One of the informants is a developer of digital solutions for public transport. This could provide us with good insights into what is essential when developing systems to support decisions in public transport. Furthermore, the five other informants were from organisations in the public transport sector, varying from private and public actors. By selecting informants from both private and public sectors, we aimed to get insights into the sectors' differences. The role of the informants we interviewed was directly related to decision-making and data, comprising IT professionals and non-IT workers.
This selection could also provide us with great insights into social aspects of data-driven decision-making, such as culture, knowledge, and maturity.

3.3 Data collection

The study's interviews were conducted in two rounds. Firstly, we conducted two interviews as a foundation for further interviews. Based on the results of these interviews, we re-structured and further developed our interview guide to gathering as detailed data as possible. The interviews were conducted openly, where the informants got to know the study's purpose beforehand. Different organisations and roles in our interviews made it hard to follow a structured interview where predetermined, standardised, and identical questions are used for each informant. Therefore, we opted for a semi-structured interview form. Semi-structured interviews have a list of themes to be covered and questions to be asked, but the order can be changed depending on the flow of the 'conversation'. Additional questions are also allowed if the informant brings up issues we have not prepared. A semi-structured interview gives the interviewee more freedom to speak freely and bring more detail to relevant themes (Oates, 2006). Our semi-structured interview guide can be found in appendix 9.1.

3.4 Data analysis

The phase of analysis was already started during the interviews, where thoughts of connections were noted. This made it easier to gather the different connections from the transcriptions. The rest of the data analysis was conducted based upon Oates' (2006) approach for qualitative analysis:

Transcription of interviews

After the interviews were conducted, the conversations were transcribed, and the informants were given the possibility to review the transcriptions. This is because they can then provide further relevant information or remove parts of the interview they do not want to be part of the study, and, furthermore, help validate the interviews (Oates, 2006).

Analysis and categorisation

After the interviews were transcribed fully, we thoroughly went through all the transcriptions to spot interesting and useful findings related to our research questions. The findings were then organised and categorised in a standalone document. We made tables for each category and linked to several quotations from the different interviews to get a better overview of the different themes. This made it easier for us to present our findings.

The standalone data analysis document was organised using the three different types of decisions presented in the literature review: Operational decisions, tactical decisions, and strategic decisions. In addition to these, we included maturity, knowledge, culture, wishes for future improvement on decision-making tools, and challenges, as these are essential aspects to include in this research study.

3.5 Validation of findings

As a measure of validity in the study, the interviews were recorded where the respondents allowed this. The audio recordings ensured that the content of the interviews was preserved and understood afterwards, thereby ensuring that the content of the interviews was valid. In addition, the respondents in the respective interview rounds were interviewed based on a similar interview guide, which also ensured that we asked the respondents the same questions. This contributed to further validity in the interview rounds (Oates, 2006). After the data was analysed, we assessed whether our findings were valid according to our problem definition. Our categorisation assessed this and whether the related information could relate to our problem definition.

We ensured that our subjectivity did not 'colour' the results by having an openness when analysing our data. Furthermore, the findings were discussed with fellow students and professional employees at our university without compromising anonymity. Transparency was important throughout our data collection and analysis process, which led to an objective discussion and conclusion. To secure relevance in the study, many discussions with our supervisor were conducted; we also discussed with other professional employees.

3.6 Additional data collection and analysis

We find our research topic interesting. It is highly relevant for today's investment in public digitalisation as a community, especially when looking at the available literature relating to our subject. Therefore, we investigated where the Norwegian government's opinion on digitalisation currently stands and what they find essential to invest in for a better future. To find literature on this subject, we investigated public reports from the government. In total, we used four reports in our additional data analysis. Two of these reports can be found directly on the government's website. The first report explains the importance of investing in a sustainable data-driven economy and innovation in the society (Det kongelige kommunal- og moderniseringsdepartementet, 2020). The other report from the government we analysed was a report focusing on the public transportation sector in Norway, purposing an action plan to move forward for the public transportation sector (Samferdselsdepartementet, 2018). The third report from Entur focuses on AI and data use; to deliver better services, the need for more transport data, including data from weather, season, day, traffic, roadwork, events, and more (Entur, 2019). The fourth report points to the need for better data in the public transportation sector, looking more specifically into the specific data needed to improve data-driven decisions in this industry (Transportøkonomisk institutt, 2014). These four reports are chosen because they pay attention to the subject "public transportation in Norway", but they all raise different perspectives, which is valuable information to utilise in our research study to better understand data-driven decisions. We also find these reports valid; this is because acknowledged and well-known public institutions produce the reports. The focus on public investments in supporting data-driven decision making has also been confirmed during our interviews by the informants, which validates these reports. The reports have also been utilised to validate the information obtained in the interviews.

3.7 Research ethics guidelines

When doing qualitative social-science research, we want to gather information from people representing a specific role within an organisation. Therefore, it is essential to follow set ethical guidelines that researchers need to abide by to respect privacy and confidentiality to the actors involved (Creswell, 2011).

The informants have been informed about their rights before their interview. The interview is voluntary to participate in. They have been given the opportunity to withdraw from the interview at any time if they no longer wish to participate, without explanation. The informants can at any time in the study withdraw their contribution if they want to.
The informants must give their informed consent to participate in the study. This is also repeated orally before interviews with the informants. Where we also tell the informants about the following:

- Who we are and what we are studying. The purpose of our study, the reason for doing the study and what results we expect from this study.
- Description of how the interview is structured and how much time we expect the interview to last.
- Explanation of how the respondent can move forward if they decide to withdraw their contribution.
- How their data will be used, and how we will keep their anonymity a priority.

Confidentiality

In the information note sent to all informants prior to the interviews, we informed them about the following: All personal information will be treated confidentially. Audio recordings and notes taken during an interview would be transcribed and stored at a safe place where only the project members and supervisor have access. The information will be anonymised and will not be linked to the informant's information. We want to refer only to job titles unless this is strongly undesirable. The names of the informants and the organisations will not be published concerning our thesis. The project will finish in June 2021. By the end of the year 2021, all data material and related personal information will be deleted.

4 Research context

This chapter will describe the setting where we conducted the research and present an overview of our informants.

4.1 Public transport

Public transport is a common name that characterises transport systems available to everyone. Public transport is often organised with fixed routes and fixed timetables typically available through bus, train, ferry, plane, and tram. This study focused on public transport organisations operating with buses and ferries, emphasising buses. Public transport differs distinctly between Asia, North America, and Europe. In Asia, private and publicly traded mass transit conglomerates typically operate public transportation systems. In North America, most mass transit authorities operate under local government control. In Europe, public transport is operated by private companies or governments. Public transport services can be made profitable by charging flat-rate fares or by using pay-by-distance routes. Services can be fully profitable if they have high usership numbers and good farebox recovery ratios. They can also be regulated or subsidised depending on local or national taxation. This study focuses on Norwegian public transport, which consists of both private companies and public sector agencies. In Norway, the private organisations in public transport are subsidised and receive additional income from, for example, ticket sales.

4.2 Data sources

In this study, we conducted ten interviews with eight informants from six different organisations. The informants consisted of several roles with direct relationships to decision-making and data. An overview of respondents is shown in the table 2 below:

Table 2 - List of informants

Informant #	**Organisation type**	**Role**
1	Developer organisation	Chief supply chain officer
2	Developer organisation	Developer
3	Public sector	Advisor
4	Private sector	Team leader
5	Private sector	Digital leader
6	Public sector	Area and transport leader

7	Public sector	Production's manager
8	Public sector	ICT-leader

The eight informants are from six different organisations. Informants 1 and 2 are from the same organisation, and 7 and 8 are from the same organisation. This provided us with other viewpoints on the same topics within organisations. Informants 3 and 4 were interviewed twice for getting more detailed descriptions and deeper insights on the research topic.

Table 3 - List of public reports

Report	**Author**
Bedre data for kollektivtransporten (Better data for the transport sector)	(Transportøkonomisk institutt, 2014)
Data som ressurs— Datadrevet økonomi og innovasjon (Data as a resource— Data-driven economy and innovation)	(Det kongelige kommunal- og moderniseringsdepartement, 2020)
Handlingsplan for kollektivtransporten (Action plan for public transport)	Samferdselsdepartementet, 2018
Entur om AI og bruk av data (Entur about AI and use of data)	Entur, 2019

As a supplement to the informants as data sources, we used four public reports from the sector for further data analysis, as shown in table 3. Because our research focuses on public transportation, we turned to public institutions to further validate our qualitative findings.

5 Results

In this chapter, we will present the findings from this research. Different findings will be highlighted with quotes from our informants, and others will be presented in tables and models. All informants were picked based on their position in the different organisations. Based on these findings, this study's research question and sub-questions will be answered. This chapter will first present the identification and categorisation of different decisions. Thereafter, we will present the different challenges we identified related to knowledge, maturity, and culture. Lastly, we will present our secondary results comprising public reports. The secondary results provide new valuable data. Additionally, it helps us validate the qualitative results from our interviews.

Our thesis focuses on decisions. Therefore, as mentioned in the method chapter, we decided to categorise and define different decisions. This resulted in utilising three main categories of decisions as predefined categories from the literature: (1) operational decisions, (2) tactical decisions, and (3) strategic decisions.

One of the goals of this thesis was to get an overview of current decisions linked to data sources in public transport in Norway. Therefore, our first subchapters will be based on the different decision types to get a clear overview of today's decision practices.

5.1 Identification and categorisation of different decisions

In this subchapter, we will explain and visualise the findings related to different types of decisions and their different data sources.

The table below gives an overview of our findings in relation to current decision practices in public transport. Table 4 shows data sources, the data in the sources, and the different decisions related to the data.

Table 4 - Overview of data sources and decisions in public transport

Data source	**Data**	**Decisions**
Real-time data	Passenger data, counting data, stop times, time between stops, sales data, passenger kilometres	Increase / decrease departures, reporting
External data	Car passes, population figures, road reports, external needs	Detour, increase / decrease departures, evaluation, estimation, reporting
Accounting	Sales data, transaction data, ticket	Ticket handling, reporting, evaluation
Statistics / historical data	Statistics from real-time systems, accounts, route data, area data	Improvement, change of route / line / area, increase / decrease departures, adjustments, assessment, evaluation, estimation

External requirements / criteria	Sustainability goals, passenger growth, green travel, innovation	Decide on goals and objectives, strategy

In the next subchapters, we will explain these decisions related to data in the different categories of decisions.

5.1.1 Operational decisions

In our interviews, we identified several operational decisions from the organisations our informants work in. We also gained knowledge of what data sources they use for different operational decisions. This subchapter will further highlight different operational decisions and their data sources.

One data source that was very central to all informants was real-time data from real-time systems. One informant from a public sector organisation commented: *"We can call it operational decisions concerning the real-time system. Here we map when and where delays occur, when there is a need to adjust the route, etc."*. Here we see that the real-time data is used in decisions about delays and route adjustments. Another informant from a public sector organisation added: *"They can see in real-time if the buses are delayed, how many passengers are on board, and related data, that are important to communicate with them. For example, if there is a need for some detours, if there is a queue in some areas, and such type of thing"*. Here we see that real-time data is used to determine detours as well as reporting information in the organisation. The same informant noted: *"As a consequence of the real-time system on the buses - through that system a ton of data is generated, how fast they drive, time duration between different stops, in addition, over the last couple of years we have implemented passenger counting system onboard in the buses, where they have full control over how many passengers are on the bus at any given time. With this, we can send out more buses, if necessary, for example"*.
Further, the informants explained that the real-time systems provide extensive data. Passenger counting, delays, and time duration between stops provide good audience information to the public. It also provides great data for supporting decisions, such as increasing or decreasing departures. With this data, several of the informants also added that they know where passengers embark and disembark the buses. With all this information, it is easier to assess resources. We see that real-time data captures a significant amount of data, thus supporting several critical operational decisions.
Further on, in addition to real-time data, we see the importance of external data to support operational decisions.
An informant from a private sector organisation explained: *"If a public road is closed, we already know in advance whether the road is closed or not because the road administration (Vegvesenet) will send out to a warning to everyone who uses the road commercially, preferably two weeks in advance. Information about detours is also provided"*. Here we see an external data source used to determine and report detours. Another informant from another private sector organisation commented: *"Because the product we deliver is under the*

auspices of us to deliver people from A to B for another product, for example air travel. Then we are dependent on data, in this case, from an airport". It is further explained that this external data is used to determine a short-term increase or decrease in travels to or from this destination.

An informant noted: *"Customers buy tickets. And sometimes we are so unlucky that we get into a situation where customers have ended up making mistakes. And then we have to offer credit, for example, a free ticket".* All informants similarly mention this. The ticket system is used to validate purchases but can also be used to treat mistakes. The ticket system is also used in collaboration with other data sources in reporting, e.g., the economy department. *"We have two ticket systems. One physical that is on board the bus provided by a company; we also have the mobile tickets which is an independent system we also gather sales data from. In addition, we have started collecting transaction data from the various acquirers, to check sales data against what is flowing into the account".* A public sector organisation stated this. Based on our findings, we see that there are vast amounts of data used to support different types of operational decisions.

Another informant also commented on a desire for dashboard functionality for an operational decision: *"The first-line workers on our ferries have a handheld device they use to scan tickets. There could have been so much information on this screen that could have been useful to the person using it. (...) A dashboard solution that could visualise data would be beneficial".*

Below, in figure 4, is a model we developed of the current practices of operational decisions in the public transport organisations we interviewed. The model is also supported by findings from the public reports presented later in the results.

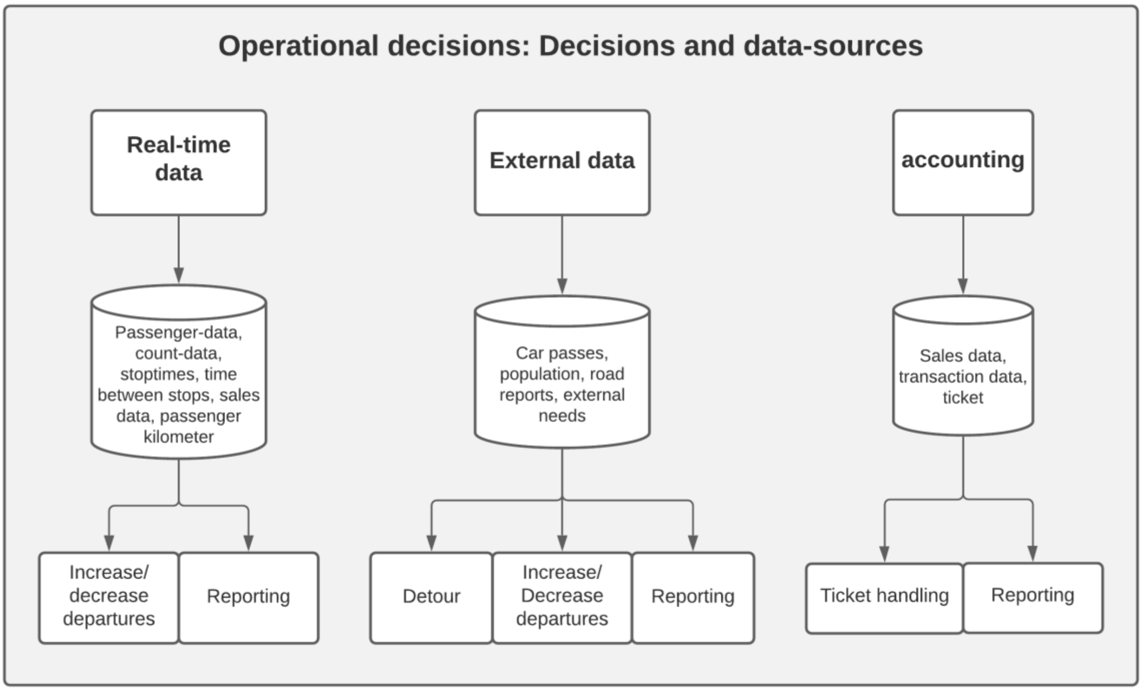

Figure 4 - Overview of operational decisions in public transport

In this model, we see three different data sources: “real-time data”, “external data”, and “accounting”. Based on the findings from our interviews, we see that the “real-time data” data source contains data such as passenger data, count-data, stop times, the time between stops, sales data, and passenger kilometres. This data supports operational decisions such as the increase or decrease of departures and reporting information.
The “External data” source contains data such as car passes, population, road reports, and external needs. This data supports operational decisions such as detours, the increase/decrease of departures and reporting. The “accounting” data source contains data such as sales data, transaction data, and ticket data. This supports operational decisions such as ticket handling and reporting.

5.1.2 Tactical decisions

In this subchapter, we will provide an overview of our findings in the interviews regarding tactical decisions.
It became apparent that data from accounting was critical towards several decisions, such as evaluation and pricing. Accounting data consists of sales data, transaction data and ticket data. These data points can help the public transport organisations evaluate their economy and the pricing of their products/services.
External data plays a significant role in tactical decisions as well. Seasonal products, such as bus routes to and from ski resorts, are heavily dependent on this. The public transport organisations are in direct contact with these external organisations. *“We ask them what their goals are this year, how many visitors they expect and how many they want us to supplement”*. The data and information from the external organisation will be the basis of a seasonal product.
Further on, as mentioned under operational decisions, routes, such as to and from airports, are dependent on external data from the airport itself. *“A challenge, on the other hand, is, for example, on the airport bus we do not have seat reservations, we only have a ticket that lasts one day. This makes a challenge in the form of not knowing how many passengers will be on each bus departure, therefore, we do not know how many buses we must put in. To mitigate this challenge, we must use statistics. The statistics we use are prepared together with the airport, which tells us how many people will arrive with the planes”.*
“When developing and implementing new bus routes, there is a lot that needs to be considered. Is it a residential or commercial area? How is the traffic situation? How will this affect other bus routes?”. All informants added similar statements. We see that the need for external data is critical to implement certain tactical decisions successfully. The population of certain areas is needed to assess new products, external needs from external organisations affect the different products critically, and more.
Further on, the real-time data from operational decisions provides a great data source for tactical decisions - statistics and historical data. An informant from a public sector organisation added: *“We have an example with our ferries where we have increased the frequency of departures on two lines the past couple of years. We implemented this because of predictive statistical data”*. *“We take out reports called boarding reports where you can see which stops customers are boarding on, to be able to see a little about which sections can*

be changed if there is poor occupancy in some areas". Real-time data provides detailed statistics and historical data that can also be used for estimation when data is missing, as mentioned by a public actor informant: *"If the data is invalid, we estimate data for each stop based on historical data. This is because we have concluded that estimated data is better than missing data"*. Statistics and historical data provide an excellent basis for tactical decisions regarding changing routes/lines, increasing/decreasing departures, and continuous improvement through evaluation and adjustments and estimations. Below, in figure 5, is a model we developed that models the data sources, their corresponding data, and their decisions.

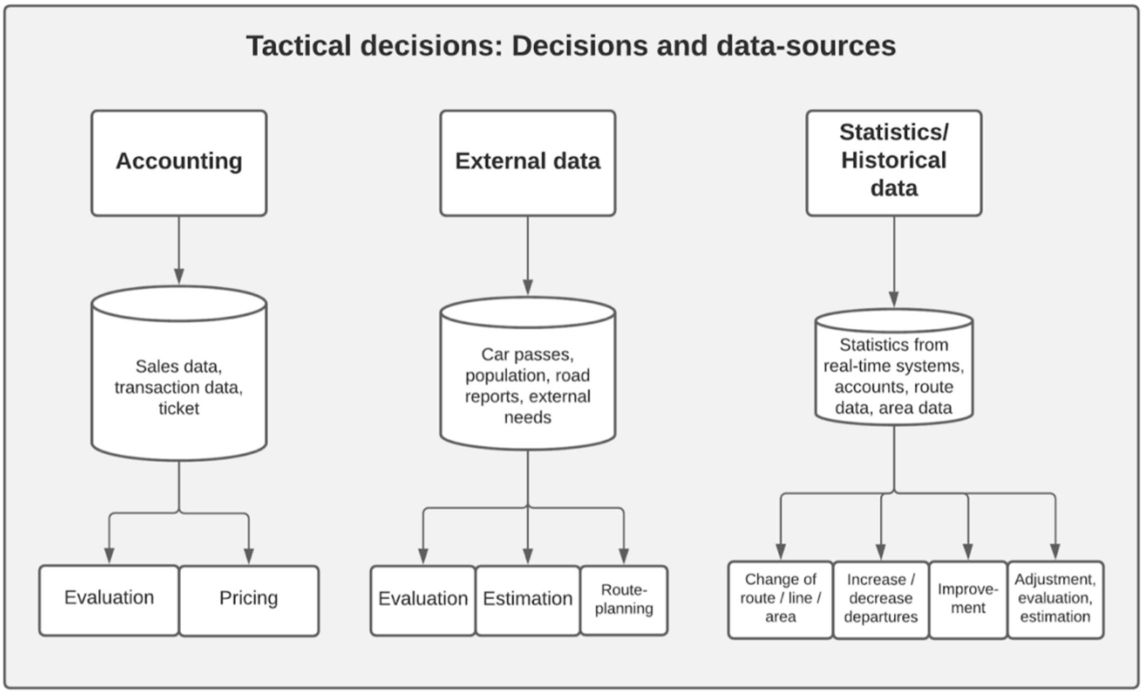

Figure 5 - Overview of tactical decisions in public transport

The data source "Accounting" contains data such as sales data, transaction data and ticket data. This supports tactical decisions such as evaluation and pricing. Furthermore, the data source "External data" contains data like car passes, population, road reports, and external needs. This supports tactical decisions such as evaluation, estimation, and route planning. "Statistics and historical data" contain statistics from real-time systems, accounts, route data and area data. This model is mostly based on the findings from our interviews but has also gotten input from the public reports that will be presented in chapter 5.3.

5.1.3 Strategic decisions

This subchapter will provide an overview of our findings involving strategic decisions from our interviews.

It became apparent in our early interviews that strategic decisions in public transport are not an entirely internal decision process. Through our interviews, we see that strategic decisions first come as external requirements or criteria from external factors, such as governmental institutions, before these requirements and criteria are supported with decisions through statistics and historical data.

"You can say that the guidelines for these strategic decisions come externally, for example that it is the UN's sustainability goals that are behind it, and then there is the regional plan, and then we are part of the tools when it comes to cutting emissions in this region. Furthermore, the public transport sector is a significant contributor, and we can have a strong influence on this". This is a general sentiment across all informants.

As mentioned, guidelines for strategic decisions come externally; then, it is up to the public transport organisations to achieve these. To do this, decisions such as assessment, improvement, increase/decrease of departures, and routes/lines and areas are made. A public actor informant noted: *"There is much pressure to get passenger growth. To do this, you increase the offer where you have the greatest potential, then you cut where you have the least potential. This is a strategy that often leads to more passengers"*. It also became apparent that many of the private sector public transport organisations depend on subsidies from government institutions, as they work as "their tools".

Below, in figure 6, is a model that visualises how strategic decisions in public transport organisations work related to data and data sources.

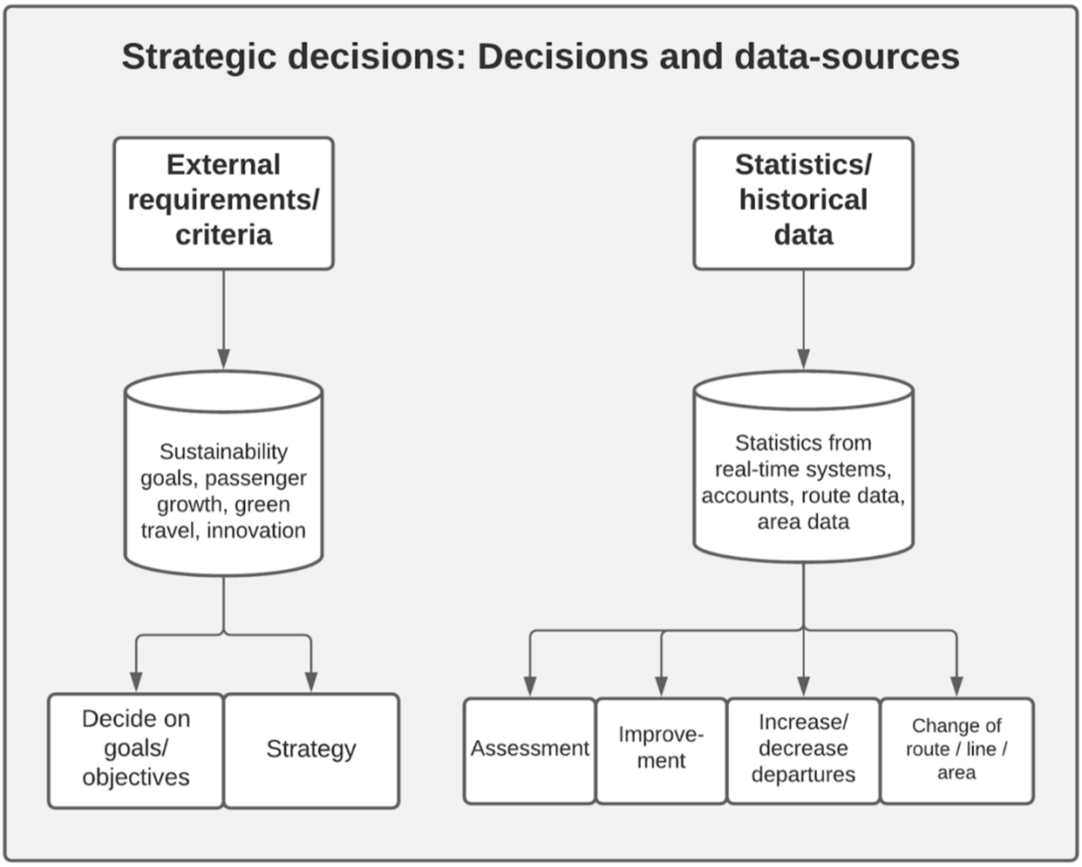

Figure 6 - Overview of strategic decisions in public transport

As we see in the model, strategic decisions have two data sources: "external requirements/criteria" and "statistics/historical data". The external requirements and criteria contain data and information such as sustainability goals, passenger growth, green travel, and innovation. These requirements/criteria support decisions as deciding on goals and objectives, and decisions regarding strategy. Statistics and historical data support decisions as assessment, improvement, adjustment of departures and change of route, line, and area.

5.2 Knowledge and maturity - challenges

We identified several key challenges in our data material comprising lack of standardisation, lack of knowledge sharing, silo-based architecture and an infrastructure not supporting knowledge sharing.

To answer our research question about how public transport can improve data-driven decisions, it is essential to identify underlying factors. We knew from our literature review that several underlying factors, such as knowledge, maturity, and culture, are essential to achieve better organisational performance through data-driven decisions fully. This subchapter will provide an overview of our findings in relation to knowledge and maturity and challenges and limitations from our interviews.

Our informants consisted of municipalities and other public transport organisations. It became apparent that the data-driven decision-making practices were different in the various organisations. A public sector informant noted: *"It is often the case that the reports that are made are generated as an order from a politician or a leader to support their existing decision, instead of evaluating data and making a decision based on this. It is a biased process"*. This affects the overall maturity of the organisation. *"Some of the decisions will be made despite the lack of good data - good enough insight"*.

Despite the differences, challenges in private sector public transport organisations are apparent as well. *"Unfortunately, there is a lot of back and forth while considering decisions, and we might often find data to support what is already decided, rather than the other way around. I can say that this is a general problem with everyone who uses data"*.

We see that there is a challenge with the foundation of data-driven decisions. Where data should be analysed and applied to decisions, it is often done the other way around. Furthermore, knowledge and culture are significant challenges. First and foremost, the age gap was brought up in the interviews as a challenge. The public transport sector is under continuous technological development, and the older generations tend to fall behind. Younger generations do not have the complete understanding of the domain as the older generations have. *"It took about a year before I somehow really understood how public transport worked. So, anyone can not just start chewing through this data because they need to understand how things actually are connected"*.

In the municipalities, it became apparent that knowledge sharing is a significant limitation. *"So, it quickly becomes that if we are to solve a task, we do it internally in the department. We do not bring in resources from the other departments, and I consider that a weakness"*.

One of the most critical challenges and limitations we uncovered in the interviews was a lack of standardisation. A public sector informant explained: *"Here we also have a challenge, that we have not been able to standardise anything. So, who takes out the report, what dates are chosen and what data is used, and how one analyses it matters a lot. We who work with*

statistics want to standardise this so that it is the same treatment no matter which area you analyse". This was a general sentiment across all informants.
We see that a lack of standardisation can create different outcomes in decisions. This, combined with the challenges and limitations of knowledge, maturity, and culture, can significantly impact organisational performance through decisions.
The gathering and storage of data also prove a significant challenge. Several public transport organisations have several silos they need to navigate to gather their data. "*We have a very silo-based solution, where we have one person who only works with collecting the different data".* The informants further mention the different limitations this can generate for them. Silos brings a lack of standardisation. An informant from the public sector added: *"You do not have insight and do not get the data you need available. For example, we can come up with a smart solution that another department can benefit from, but it is not available for the other departments to retrieve that data or get the insight. No data warehouse takes care of the entire organisation".* Furthermore, even though they gather vast amounts of data, the data they collect can't always explain outcomes, as an informant from the public sector explained: *"In the public transport industry, numbers matter. Before the Covid outbreak, we had around eighty thousand passengers who travelled by bus around the county during weekdays, but the numbers were at most half of the weekdays when the weekend came. On Saturdays, it is around twenty thousand passengers, and on Sundays around fifteen thousand. So, if you compare one, for example, April, with another April, it really matters whether the month has had an extra Sunday or not. If you also add an extra holiday to the month, it has considerable consequences for the outcome of the analysis".*
We see that there are several challenges that need to be addressed to improve data-driven decision-making in public transport.

5.3 Secondary results

Our data collection method consisted of both gathering data through qualitative interviews and obtaining information from public reports from the public transport sector and messages regarding public transportation from the government. This section will present findings from public reports by presenting one report after another.

'Better data for the public transport' (Transportøkonomisk institutt, 2014) provides an overview of challenges related to data in public transport and recommends several measures to improve the data. In this public report, we gathered information on publicly available statistics and potential data sources connected to different types of public transport. Below, in table 5, is a remake of their overview of the most important statistics and data sources.

Table 5 - Overview of statistics and data sources (Transportøkonomisk institutt, 2014)

	Public available statistics	**Reported by**	**Data sources from public available statistics**	**Possible data sources**
Passenger transport on railroad	SSBs statistics about railroads, Jernbaneverkets yearly publication, NSBs yearly reports	Operator companies	Counting, ticket statistics and calculations	Equipment counting, real-time information, electronic ticketing
Express buses	SSBs public transport statistics, TØIs mapping of express buses	Operator companies	Ticket statistics and calculations	
Regional boat traffic	SSBs public transport statistics	Operator companies/ Administrative companies/ Municipalities	Ticket statistics	Equipment counting, real-time information, electronic ticketing
Bus- and local rail transport	SSBs public transport statistics, SSB Kostra, Key data from yearly reports and plans	Administrative companies and operator companies	Counting, calculations, ticket statistics	Equipment counting, real-time information, electronic ticketing
Order transport	Yearly reports	Operators, administrative companies	Counting, calculations	
Traveling habits	The national traveling habit survey (Den nasjonale reisevane-undersøkelsen)	Individuals	Calculations, raw data from the national traveling habit survey	Local traveling habit surveys, MIS-systems

This report and table provide a good overview of vital statistics and data sources in different public transport organisations and further helps us validate findings from the interviews. Furthermore, the report concludes that today's basis of data is sufficient in many cases but has further improvement potential. They recommend adjustments and changes in existing definitions and variables that will further help them standardise.

'A message to the government' (Det kongelige kommunal- og moderniseringsdepartementet, 2020) tells us about data as a resource in a data-driven economy. This message tells us that better exploitation of data will support Norway in achieving a more sustainable society with a "greener" economy. The governmental ambition is to increase the sharing of data between the public and private sectors. This is relevant to our thesis, as knowledge sharing is crucial

to achieving high organisational performance through data-driven decision-making. A "greener" economy and sustainability is also at the centre of the public transport's strategy. Therefore, this provides great input to our thesis.
'The action plan for public transport' (Samferdselsdepartementet, 2018) tells us what is to be improved and assessed in the public transport sector. This report gave us great insights into where the current focus of improvement lies. It became apparent that a primary objective was to set fixed standards for collecting data. Standards were a major part of the objectives, where they conduct continuous work to improve data throughout the sector.

Through our search for public reports, we came across a presentation from Entur (Entur, 2019). This presentation contains valuable information about how different data types can be combined to support decisions better. They added in their presentation, that to deliver better services, we need more data than only transport data.

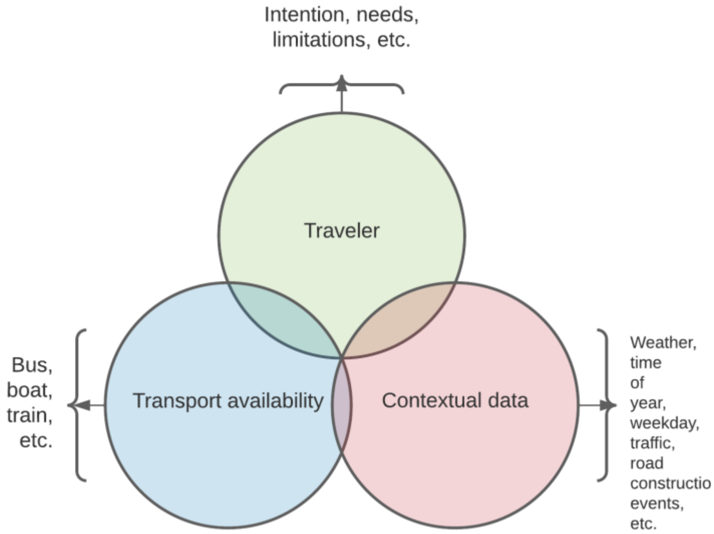

Figure 7 - Dataset to improve decisions (Entur, 2019)

Figure 7 shows an example of different data sources that can be combined to support better decisions. In this example, they gather data of a traveller: Intention, needs and limitations. They also capture contextual data: Weather, time of year, weekday, traffic, road construction, events, and more. This data combined can provide great insights to, e.g., an AI to make travel decisions for both the traveller and the public transport organisation. The different sets of data combined can help us answer our research question on how data-driven decisions can be improved in public transport.

5.4 Summary of results

We have gathered information on the different categories of decisions throughout the different interviews, ranging from operational, tactical, and strategic decisions. We have developed models that map out data sources and their data related to different decisions. Furthermore, we identified several challenges, such as standardisation and culture, that mitigate the possibility of successfully implementing data-driven decisions in public transport. Several of the findings can help us assume the maturity level of the organisations, which can help us develop a framework for better data-driven decisions in public transport. The public reports we gathered information from provided us with great insights into different data sources and statistics. They also provided us with information on what the sector is focusing on to improve. We see that the data from the public reports are coherent with our qualitative data, thus helping us validate the results. Furthermore, the context of different data combined can further help us suggest better data-driven decisions.

6 Discussion

Our data analysis and literature findings provide us with thorough directions on how data-driven decision-making can be improved in public transport. However, first and foremost, we see the significant importance of improving data-driven decision-making capabilities to improve their decisions. In this chapter, we will discuss the different findings from this study. First, we will discuss the capabilities before discussing the improvement of the decisions.

6.1 Data-driven decision-making capabilities

DDDM capabilities involve skills, culture, processes, and infrastructure. The impact of the capabilities became apparent in our literature review, where we see that the different capabilities facilitate each other. (1) Data analytics improve knowledge sharing in organisations. (2) Knowledge sharing fully mediates data analytics usage impact on decision quality. (3) Knowledge sharing does not necessarily improve firm decision quality; its impact is heavily moderated by data analytics capability and competency. (4) Data analytics competency moderates knowledge sharing impact on decision quality. (Ghasemaghaei, 2019). To maximise the potential of data, everyone encountering it must be able to turn data into insights, regardless of skill levels and fluency of data.

In the next subchapters, we will discuss the different findings related to capabilities, and propose a model for public transport to improve their capabilities.

6.1.1 Standardisation

The treatment and reporting of data lack standardisation in public transport. As we see in the results, the analysis of data is heavily dependent on who analyses the data. The analysis processes are not standardised. Furthermore, data is not available to everyone. as explained by several informants, if a department innovates or develops a great solution, other departments will not benefit from it, as there is no data warehouse in place. It seems many public transport organisations suffer from silo-based solutions, where data is not retrievable from one but several locations.

Based on our findings, we argue that most public transport organisations are located somewhere between the application silo architecture stage and the standardised technology architecture stage of Ross' (2003) model of strategic implications of IT. The organisations lack comprehensive standardised technologies and are hindered in their infrastructure by application silos. Through our data collection, we see that most public transport organisations are working to standardise their technologies and develop data warehouses. However, they are not reaching their goals just yet. The application silo architecture stage has some benefits; the strategic goal is local optimisation, which the organisation often will naturally align with. Albeit there are benefits, there are several downsides. When an organisation has application silos, innovation becomes more complex, as linking new applications to relevant and related systems becomes more challenging over time. In the end, the applications might end up as a burden rather than a blessing. As time goes on, allowing variety and innovation in silos will make organisational performance hard to achieve and expensive.

Public transport organisations need to step away from application silos and enter the world of a shared infrastructure.

Silos make it hard to gather data, which again can result in unstructured data. Unstructured data can lead to unstructured decisions, often based on intuition rather than the data itself. Unstructured data can also be incorporated into structured decisions, where the unstructured data is applied through pre-defined procedures (Harrysson et al., 2014; Intezari & Gressel, 2017). Based on findings from the interviews, several IT professionals agree that decisions are decided before they gather data to support them. Instead of gathering data and applying them to decisions, we argue that many of their decisions are unstructured decisions based on unstructured data - intuition-based decisions. We also find that the development of data-driven decision-making is problematic because of political factors. The industry we are researching is heavily guided by the government's sustainability accords and environmental goals that need to be met to be subsidised. The public transport sector is heavily subsidised and controlled based on these agreements and goals. According to our informants, this is an obstacle to overcome when moving to a more data-driven decision-making approach and causes a delay in achieving a higher architecture maturity.

6.1.2 Knowledge and culture

Based on the literature, we know that both knowledge and culture have a mediating role in decision-making. Data-analytics capabilities mediate its impact on organisational performance, but knowledge and culture have a significant role in improved data-driven decision-making capabilities.

It seems like many of the organisations we interviewed have knowledge sharing processes and practices. They share information between employees, and to some extent, between departments. But all knowledge that is generated in one department does not always reach another. This suggests a sharing culture but a lack of supporting infrastructure.

Furthermore, the capability of applying knowledge to decisions is an important aspect. In our interviews, we interviewed both IT professionals and non-IT workers. There was an interesting finding that there was a particular disagreement on how decisions are made between the different roles. Non-IT workers added that data is analysed and made into decisions. In contrast, IT professionals commented that it is the other way around - making decisions and finding data to support this. This indicates that the knowledge of data-driven decision-making needs to be addressed. If there is a good knowledge culture, employees are more likely to teach each other knowledge that would otherwise not be shared, which again provides employees more data to make better and revised decisions (Chen, 2010). We find that data innovation is lacking when researching organisations.

On the other hand, the Norwegian government proposes that it is crucial to invest in the digital economy, but this can be challenging for the organisations we researched. To help overcome this obstacle, we need to look deeper into knowledge management. One goal is to become a more innovative organisation. During the development of new products, an innovative climate encourages employees to explore their creative side. This environment also supports them in developing new ideas and approaches to work. Knowledge management activities help firms develop new knowledge and improve their innovativeness. They also contribute to the development of new products and services (Chen, 2010). When interviewing our informants, we found that decisions are often made intuitively based on experience from senior employees. Our informants informed us that this is a typical pattern in public transport. Based on the literature found, this is an obstacle when developing a better knowledge culture. The organisation's structure may constrain the employees from combining their various knowledge sources for developing new products or services. On the other hand, less formal structures could encourage employees to ask for different perspectives and develop their own ideas, leading to better innovation and better decision making (Shalley & Gilson, 2004).

6.1.3 Improving data-driven decision-making capability

This section will propose a framework on how public transport should improve their data-driven decision-making capabilities. Culture is the most critical enabler for enhancing knowledge sharing in projects. It enhances the stability of organisations and serves as a sense-making device that can guide and shape behaviour (Oyemomi et al., 2019; Staadt, 2015).
As previously mentioned, our interview findings suggest that the public transport organisations lack technology standardisation and, to some extent, suffer from silo-based infrastructures. Furthermore, they lack standardisation in analytic processes and need to develop a culture further to facilitate this.
Inspired by Gill's (2014) framework for improving data-driven decision-making capabilities in education, and Ross's (2003) architecture stages, we developed a model emphasising the challenges we identified in the interviews, highlighting them as objectives to improve data-driven decision-making capabilities.

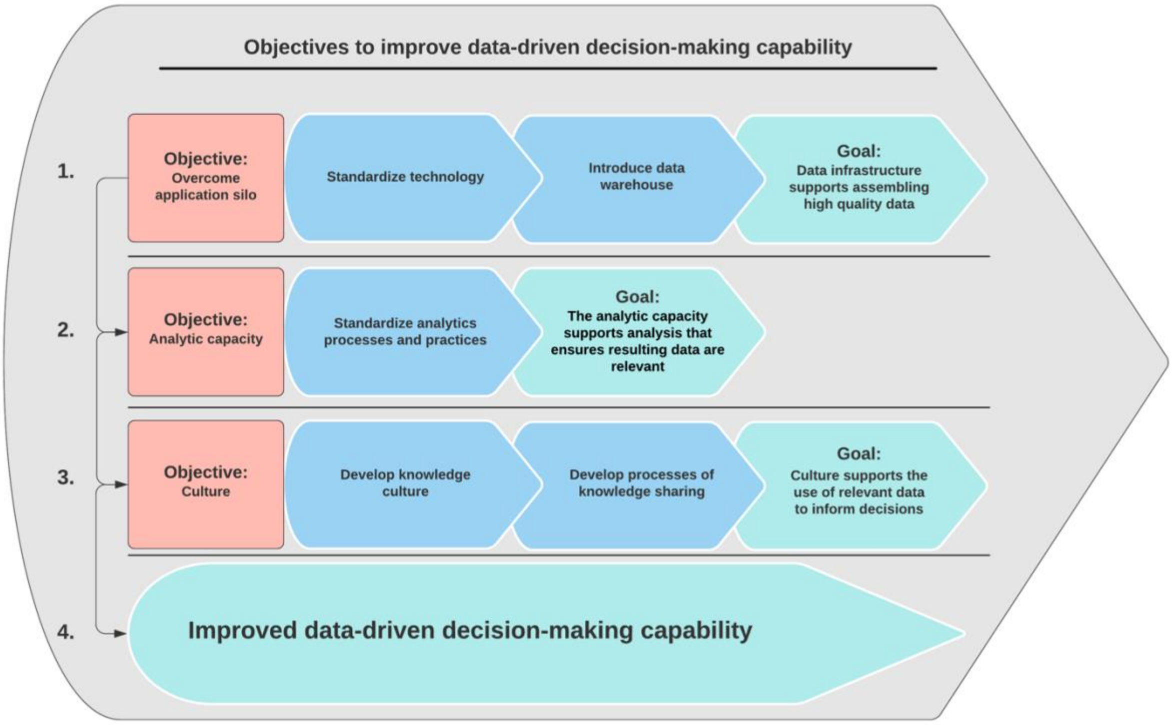

Figure 8 - Improving data-driven decision-making capability

Figure 8 shows the different goals the organisations must achieve to improve their data-driven decision-making capabilities, which will facilitate improved data-driven decision-making.

Objective 1 - Overcome application silo: The first objective is to overcome application silo by standardising technology and introducing data warehouses. This makes the data infrastructures support assembling high-quality data. The new infrastructure will also make innovations more accessible and new applications less of a burden (Ross, 2003).

Objective 2 - Analytic capacity: In this objective, the standardisation of analytics processes and practices must occur to make the analytic capacity support analysis that ensures the resulting data are relevant and diagnostic. As mentioned in the interviews, the current analytic processes are not standardised, thus making data analysis heavily dependent on the person that conducts the analysis, as it will differ from each person's approach. A practice like that will not ensure that the resulting data are relevant and primarily not diagnostic. Diagnostic data is data that is correctly measured and will provide the same results if done repeatedly (Gill et al., 2014).

Objective 3 - Culture: In this objective, the public transport organisations must develop a knowledge culture and knowledge sharing processes so that the culture will support the use of relevant data to inform decisions. Suppose an organisation has built up good knowledge management practices (knowledge culture, sharing). In that case, their application of other related aspects, such as big data and data analytics, could significantly improve organisational performance, improving their competitive advantage (Shabbir & Gardezi, 2020). Knowledge culture and knowledge sharing will also facilitate the infrastructure. The infrastructure also facilitates the culture - data analytics improves knowledge sharing, and knowledge sharing mediates data analytics usage impact on decision-making quality (Ghasemaghaei, 2019).

The order of the objectives is crucial. One cannot standardise analytics processes or develop a good knowledge culture without a supporting infrastructure; thus, overcoming the application silo is objective one. Furthermore, you do not want a culture to promote non-relevant and non-diagnostic results from analytics. Thus, you need to standardise analytics processes and practices before developing the culture.

By achieving these three objectives, the organisations will improve their capabilities for data-driven decision-making, thus making it an easier task to develop further and improve decisions.

6.2 Differences between the public and private sector

Our selection of informants contained both actors from the public and private sector in public transport. Early on, it became apparent that there are some significant differences in how the organisations from the different sectors operate, thus affecting decision-making processes. The public sector comprises organisations that are owned and operated by the government, both national and local, while the private sector contains private enterprises. "Private, for-profit organisations have smoother decision-making processes. Public organisations experience more turbulence, interruptions, recycles, and conflict" (Nutt, 2006). Organisations in the private sector sell and provide products and/or services to consumers in markets to generate wealth for shareholders. The typical public sector agency contracts for services and collects information about the needs of people that calls for public response. These are distinct roles with distinct differences that suggest a significant difference in expectations and accountability, suggesting a difference in decision-making practices (Nutt, 2006; Papadakis & Barwise, 1998).

In our interview and data analysis processes, we uncovered some differences. First and foremost, it is the political nature the public sector organisations find themselves in, as one of the informants from a public sector organisation commented: *"Often the reports that are made (data analytics reports), are generated on orders from politicians. Not necessarily to evaluate the data, but to support existing decisions"*. This suggests practices that contradict the nature of data-driven decision-making, where data is supposed to "drive" and implement the decisions, not the other way around. While public sector organisations conduct decisions based on political decisions and conditions, the private sector conducts decisions based on profit, organisational performance, and competition. Differences also come from laws. Public organisations are not allowed to compete for customers. The area of service is stipulated, thus not grown from marketing. The creation of a duplication of services would be regarded as undesirable. Public sector decision-makers often use this concept to enhance cooperation among various players. In a private-sector organisation, ideas are often held close and are usually not shared among other parties. This situation is different from a public sector organisation where the public demands transparency and collaboration. (Nutt, 2006).

The external environment of a public sector organisation is often full of political considerations. The views of opinion leaders, manipulation by legislators and interest groups, and opposition to an agency's privileges are more important than issues of economy, which again are crucial for private organisations. The characteristics of public and private organisations are often linked to goals and authority limits. A public organisation has multiple goals and can be controversial or popular, or both. The demands made by interest groups, turbulence in projects, and manipulation by stakeholders and other parties develop a complex and challenging set of expectations, which often conflict with each other. Being able to deal with clients and providing services is often more important than efficiency in such organisations. The use of efficiency and cost-reduction measures becomes less valuable as subsidies become more important. Uncertainty about goals and objectives can affect the performance of public sector organisations. It can also affect the efficiency of their operations. The more public an organisation is, the harder it is to manage. The lack of goals and subsidy criteria can make it difficult to identify alternatives to inefficient management (e.g., cost-savings measures). Having goals and subsidy criteria can also make it difficult to evaluate the effectiveness of alternatives (e.g., efficiency measures). The public sector has weaker power bases and lacks the funds to make significant investments in managed systems (Nutt, 2006).

There are differences on many levels, thus making decision-making practices being considered and leveraged differently. Even though our informants consist of private and public sector organisations, they all operate in public transport, which is heavily controlled by the public sector. Private actors in public transport often rely on subsidies from public sector agencies to provide their services. One of the private sector organisations added: *"In 2019-2020, around one-fourth of the turnover was based on subsidies"*.

When it comes to decision-specific practices, at the higher decision levels (strategic decisions), the private sector organisations make decisions based on external regulations, demands and/or criteria based on sustainability goals and further developments in infrastructure in a municipality. The differences are more evident on the lower levels of decision-making practices (tactical and operational decisions). The private actors make decisions based on goals and turnover, whereas public actors have several more considerations.

The difference has several implications towards our proposed framework containing objectives to improve data-driven decision-making capabilities. The standardisation of analytic processes and practices will be hard to implement. The political nature might not allow a complete standardisation as of today's situation, where decisions are made by politicians followed by identifying supporting data. To implement standardised processes in public sector organisations, political decision-practices must change, which might contradict political processes that are based upon public desire and wishes. Even though a complete standardisation of analytic processes might be challenging to implement, we still suggest implementing it on the lower levels of decision-making; tactical- and operational decisions. Furthermore, we argue that the differences bring little to no implications for technology standardisation and culture development, as these are factors that are already worked on in public organisations, as in private organisations.

6.3 Improving decisions

This study has provided findings towards data-driven decision-making capabilities and decision-specific data. The first step towards improving data-driven decision-making in public transport is addressing the capabilities. The informant organisations are mostly silo-based, which suggest a low architecture maturity. By maturing the architecture to the standardised technology architecture stage (Ross, 2003), the infrastructure will support assembling high-quality data. In addition to standardising the technologies, the analytics processes and practices should also be standardised. This will make the analytic capacity support analysis that ensures the resulting data are both relevant and diagnostic. Further development of culture into knowledge culture and facilitation for knowledge sharing will ensure that the use of relevant and diagnostic data is applied to decisions. When these steps are implemented, we argue that the data-driven decision-making capabilities are improved. This section will discuss the different decision levels and how they can be improved in public transport.

6.3.1 Different levels of decisions

This study divided decisions into three different categories: Operational, tactical, and strategic decisions. Operational decisions are day-to-day decisions that have a short-term impact on organisations; tactical decisions support organisations' overall strategy; strategic decisions decide on organisations' goals and objectives, and involve strategies to achieve these, thus impacting organisations long-term.

It was essential for us to categorise different decisions, as the mentioned categories involve different decision-makers, impacts, and needs. Operational decisions can involve all roles in an organisation, where, e.g., a bus driver calls for extra buses on a route because of passenger overflow, or a customer-service agent refunds a customer because the customer ordered the wrong ticket. Tactical decisions are often conducted by middle-to top-leaders, including decisions such as developing new bus routes and evaluating ferry routes. Strategic decisions are made by top-level leaders and affect the organisation and lower-level decisions long-term. During our interview rounds, we uncovered detailed information on what data sources are typically applied to the different levels of decisions (table 4). The real-time data source provides data on passengers, counting, stop times, the time between stops, sales data, and passenger kilometres. On an operational level of decisions, this supports decisions such as the increase or decrease of departures and reporting. Over time, real-time data is stored and turned into statistics and historical data which provide detailed data used for improvements, change of route/line/area, increase, or decrease of departures, and further adjustments, assessments, evaluations, and estimations on both a tactical and strategic level of decisions. Further data sources consist of external data and accounting data that supports operational and tactical decisions and external requirements and criteria that support strategic decisions.

We uncovered that the major operational decisions in the interviews are increasing or decreasing departures, decisions connected to detours, ticket handling, and reporting. The data sources connected to these decisions are thorough and well-thought. During the interviews, one of the public sector actors expressed a wish to have dashboard views on data for the first-line workers on their ferries. A proper visualisation of data could potentially support operational decisions further. Dashboards which can track and visualise data "can provide useful 'evidence-base' for planning decisions" (Engin et al., 2020). If a first-line worker on a ferry always had access to real-time data on a dashboard, preparations between departures would be more straightforward, as they would know how many passengers to expect. We argue that the data sources connected to operational decisions are sufficient for today's use in decisions, but the visualisation of data can further increase the quality of operational decisions.

Tactical decisions could benefit from visualisation as well. Visualisation tools can show data trends easier to an analyst. For example, visualisation in heat maps could easily visualise route delays, as shown in figure 9 (Lock et al., 2021).

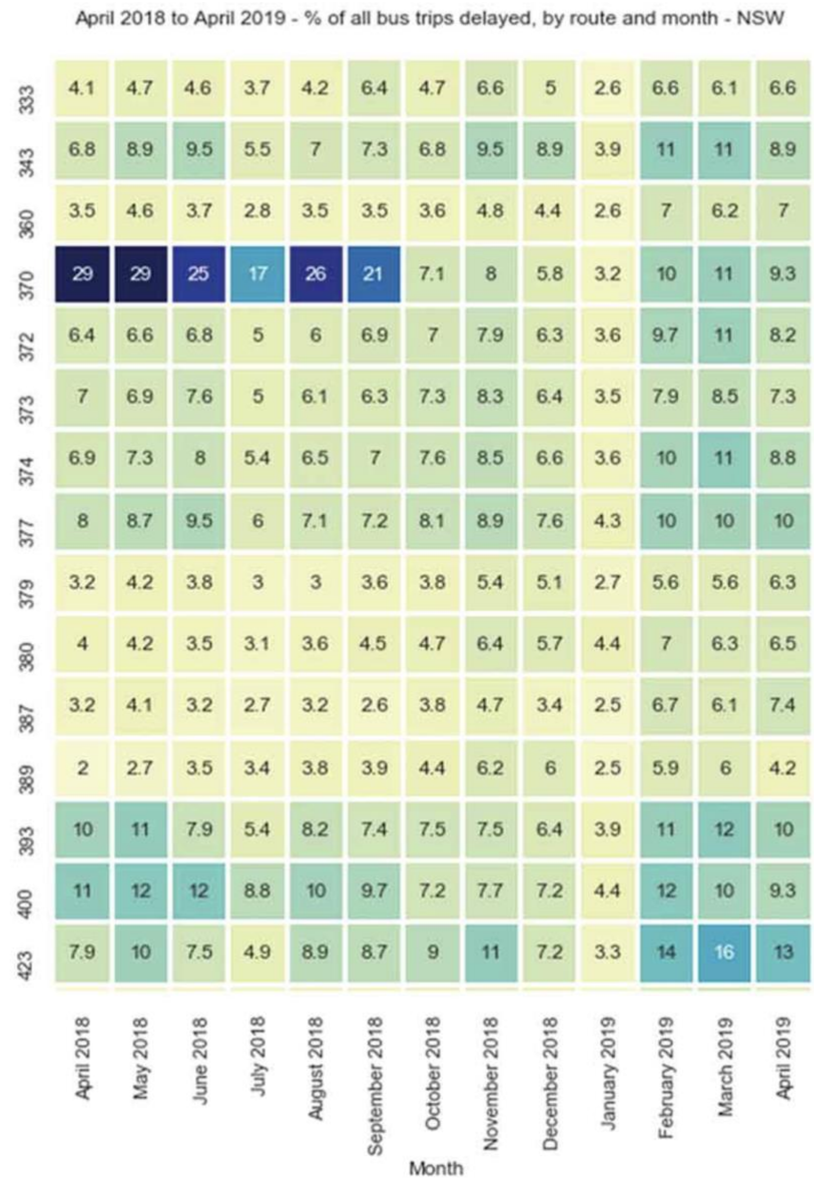

Figure 9 - Example of heat map visualisation (Lock et al., 2021)

The example shows route number to the left and months and year at the bottom. The individual cells represent the percentage of all bus trips delayed.
As previously discussed, the standardisation of analytics processes and practices is vital for data-driven decision-making capability. The different organisations faced challenges where the data output was heavily dependent on who processed the data. Visualisation tools could further mitigate this challenge, as the data combination is predetermined. Strategic decisions could also benefit from such visualisation tools as trends and KPI's are easier to spot.
We argue that the data sources related to the different decisions are sufficient for today's use. However, further, we will argue that there is an additional source that could support all the data sources and, to some extent, facilitate standardisation.

6.3.2 Contextual data

The data sources combine into great data sets that support a vast number of decisions, and it is argued that this basis of data is sufficient in many cases (Transportøkonomisk institutt, 2014). As we explained earlier, the standardisation of analytics processes and practices must ensure that the resulting data is relevant and diagnostic. We argue that an additional data source could benefit the public transport organisations in standardising analytics results. This data source is called contextual data. Contextual data is the background information that provides a broader understanding of a subject, e.g., an event, person, or item (Sisense, n.d.). Contextual data can come in the form of weather data, time of year, day, traffic, events, and more. We argue that contextual data can help standardise analytics reports by bringing context to the data. One of the public actor informants commented that analytics results may vary from month to month without them being able to explain it. In situations such as this, contextual data could provide clarity to the reports, e.g., why there were fewer passengers this April relative to last year's April. Using internal and external data sources cannot provide full context and causality without manual labour. By knowing the context of data, analytics processes and practices can become more efficient, relevant, and diagnostic, which will further back our framework of objectives to improve data-driven decision-making capability. In the example below, we visualise this by providing how the different data outputs can look like (numbers are entirely random and not provided from any source):

Passenger count for area X:

April 2019	Passenger count: 310 000
April 2020	Passenger count: 290 000
April 2021	Passenger count: 220 000

This data output provides information on passenger counts compared to the same months of different years. By looking at this without context, one might argue that the transport area has a major decline in popularity. Below, we visualise how it could look with contextual data.

Month/year	Passenger count	Weather	Holidays	Days of weekend
April 2019	310 000	20% rain	5	8
April 2020	290 000	10% rain	5	8
April 2021	220 000	5% rain	5	9

This example brings context to the picture. From this output, one could better explain emerging trends in the market, which will form an improved basis for decisions. Therefore, we argue that contextual data is a critical data source that should be implemented in all public transport organisations.

6.4 Limitations in this study

In this study there are several limitations that can affect the end-result:

- Early in the interview process it was stated that the public transport industry is hard to fully grasp. One informant added: *“It took about a year before I somehow really understood how public transport worked. So, anyone can not just start chewing through this data because they need to understand how things are actually connected”*. One clear limitation is little knowledge of how the sector operates and little knowledge of internal culture.
- The study is limited to public transport organisations operating with buses and/or ferries, with emphasis on buses. We did not manage to gather data from the train industry.
- By conducting ten interviews in six organisations, we only touch a minority of the sector.
- Only informants in positions that have a direct relationship to decision-making and data are interviewed. This limits the possibilities for views from other aspects of the organisations.
- We conducted a semi-structured literature review to identify relevant literature to form a basis for the study. The literature we identified and applied are mostly not generalisable, as they comprise case-studies of single organisations, and organisations from other countries. Even though this is a clear limitation, the literature provides great pointers towards the different aspects we are studying.

7 Conclusion

In this study, we have researched data-driven decision-making and underlying challenges in public transport to recommend improvements. To address this, we formed the research question: "How can data-driven decision-making be improved in public transport?".

The research question was answered by conducting ten interviews in six organisations, including roles directly related to decision-making and data. We analysed both data and literature and learned how decision-making works on different levels, operational, tactical, and strategic, with insights into what data sources they apply. Furthermore, we see that the public transport organisations are heavily politically controlled, especially at the higher levels of decisions. The organisations lack underlying capabilities to improve data-driven decision-making, such as standardisation in technology, standardisation in analytics processes, and culture. We have developed a framework proposing objectives on how organisations can improve their data-driven decision-making capabilities by (1) making the data infrastructure support assembling high-quality data, (2) making the analytic capacity support relevant and diagnostic data, and (3) making the culture support the use of relevant data to inform decisions.

Furthermore, we discussed using alternative methods to visualise the data for greater understanding, e.g., using heatmaps. We also propose using contextual data as a data source, as this source could potentially help the standardisation of data, as it brings context to the picture.

Data-driven decision-making can be improved by further developing its capabilities. Furthermore, additional data sources, such as contextual data, can improve the data quality, which in turn can improve the decision quality.

7.1 The study's contribution

In this study, we have investigated how decisions work in different public transport organisations. We identified decision-making processes and practices related to different data sources. Further, we identified several challenges the various organisations face in relation to capabilities for data-driven decision-making. With this as a basis, the study can be of great interest for public transport organisations in both the public and private sector. Furthermore, organisations that develop digital solutions for public transport can benefit from several aspects of the study. Other organisations can also benefit from the study, as the capabilities for data-driven decision-making are essential throughout all sectors.

In the field of information systems, this study contributes to identifying key capabilities for data-driven decision-making in public transport. It also emphasises the challenges that are faced in relation to data-driven decisions.

From an academic perspective, the study can contribute as an illustrative case in an educational setting. By showcasing how various private and public sector organisations make decisions and what factors they must consider when conducting and improving data-driven decision-making, we can better understand underlying capabilities that drive the decision-making processes. Furthermore, it can contribute to complementing the picture of differences between the public and private sector related to data-driven decision-making capabilities.

7.2 Implications for further research

This study has several findings that can be used for further research and applied in organisations for practical use. The study contributes to providing a holistic picture of data-driven decision-making capabilities in Norwegian public transport. For researchers, this study can provide a basis for further research. The study forms a basis for a quantitative study on capabilities, such as culture, knowledge, and maturity. A quantitative study could create a greater picture of the capabilities.

The study also forms a basis for further case studies. We would recommend a longitudinal case study to better understand the culture, maturity, architecture, and their development through time. Our informants added that work is in progress in several of these fields. Furthermore, this study recommends the use of contextual data to increase the quality of other data sources. This forms a basis for research on the practical use of contextual data in public transport.

Before this study was initialised, we did not know to what extent there were differences between the public and private sector in public transport. Further research studying public transport should integrate this as a significant focus in their studies, identifying differences at a higher level.

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9 Appendix

9.1 Semi-structured interview guide

Introduction

1. Present ourselves
2. Explain the informant's rights and confidentiality
3. Consent/deny audio recording and guidelines
4. Short, present the project
5. Ask the informant to present him-/herself and his/her role and organisation

Main section

Data and systems

- What data do you collect?
    - If needed, examples:
        - Collection of data related to assessments of projects
        - Data to assess efficiency
    - Where is the data collected?
        - E.g., sensors, GPS, accounting
    - Examples of how the data is used/analysed?
    - Ask about the systems they are using for their everyday operations
        - Explain
        - Wishes for improvement.

Different types of decisions

Explain the different decision-categories: Operational, tactical, and strategic decisions. Provide examples.

- Do you have examples of operational decisions?
    - Necessary data for operational decisions
        - How/where is it gathered?
        - Is the decision triggered by data? Routine?
        - How is the data applied into the decision?
    - Do you have examples of tactical decisions?
        - Necessary data for tactical decisions
            - How/where is it gathered?
        - Is the decision triggered by data? Routine?
        - How is the data applied into the decision?
    - Do you have examples of strategic decisions?
        - What data are they based on?
        - Where is it gathered?

Ask for wishes for improvement and challenges related to the different examples provided by the informant.

Challenges and limitations

- Ask about challenges:
  - When collecting data
  - Analysing data
  - Making decisions
- Ask about culture
  - Knowledge culture
- Ask about architecture (Silo, data warehouse)
  - Maturity

Ending

- Ask if the informant wants to add anything that he/she finds relevant
- Thank the informant for participating
- Repeat the informant’s rights, especially about transcript and audio recording