CHAPTER 9

Exploring data analytics adoption in public procurement: The case of Norway

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Abstract: Procurement analytics is the process of collecting and analyzing procurement data for identifying meaningful insights and aiding in effective business decision-making. The prevalence of large datasets is starting to spread high potentials across the public sector; however, an impediment to its reach and utilization orientates around the low level of data analytics adoption to exploit the full potential of this data availability. In this paper, we explore the adoption of the data science process and data analytics in procurement in the Norwegian public sector through the technology-organization-environment framework. This is achieved by employing descriptive statistics on survey data collected by the Norwegian Agency for Public Management and eGovernment, which included 343 responses across 136 municipalities, 115 state enterprises, 11 counties, and 81 municipality and state companies. Our descriptive results indicate that the organization context-related factors, such as employee competence in analytics, budget size, and top-management support for data-driven cultures, impact the organization's adoption of data science and data analytics in public procurement. The technological and environmental contexts (for example, use of digital tools, technology availability, and national policies) have no clear impact on the organization's adoption of analytics. However, our correlation analysis results show that none of the above-mentioned factors have a correlation with the adoption and use of data analytics in public procurement.

Keywords: public procurement, data science, data analytics, decision-making, Norway

Citation of this chapter: Langseth, M. & Haddara, M. (2021). Exploring data analytics adoption in public procurement: The case of Norway. I M. Langseth & J. O. Similä (Eds.), *Å kjøpe for Norge* (Ch. 9, pp. 223–256). Cappelen Damm Akademisk. https://doi.org/10.23865/noasp.128.ch9

1 Introduction

Digitalization of the public sector aims at providing enhanced services and more efficient use of resources, for both citizens and organizations alike. Digitalization has also the potential to serve as a foundation, paving the way for aiding in the decision-making process at government agencies, and facilitating increased productivity in society at large. In the past, data collection and analysis were either too expensive or deemed not worth the effort; thus, organizations only carried this out when the cause-and-effect relationship between process input variability and their desired output was obvious and substantial. Currently, with the unprecedented amount of data available today and the substantial decrease in storage and processing costs, enterprises in almost every industry and domain are focused on exploiting data to their competitive advantage, by adopting data analytics and data science environments and techniques (Elragal & Haddara, 2019; Provost & Fawcett, 2013).

At an abstract level, the data science paradigm is a set of central principles that aid and guide the extraction of information and knowledge from various types of data (Elragal & Haddara, 2019; Provost & Fawcett, 2013). Data science involves the foundations, processes, and techniques for understanding the various phenomena, trends and patterns in data, via (automated) data analytics (Haddara & Larsson, 2017; Provost & Fawcett, 2013). In a nutshell, data science is the adoption and application of quantitative and qualitative methods and techniques to solve pertinent problems and be able to predict outcomes. One of the significant revelations of today, with the vast and growing amount of data, is that domain knowledge and analysis cannot be separated (Waller & Fawcett, 2013).

Progressively, data science and analytics concepts and technologies are piercing through several domains and industries, including governments, e-business, e-commerce, healthcare, retail, insurance, and many other industries and domains (Schelén, Elragal, & Haddara, 2015). This high penetration rate is sustained by the fact that there is now a vast amount of data accessible from diverse sources, like internal transactions, social networks and web 2.0 data, spatial and GPS data, weather data, streaming data, RFID, and sensor data. One of the main reasons that leads organizations to invest in data science projects is to harvest the fruits of (big) data analytics, which, in turn, can enable what is called the *data-driven enterprise*. Hence, the basic goal of data science and data analytics is to promote data-analytic thinking, and improve and enhance the decision-making process within organizations, as normally this is of supreme interest to businesses and governments (Chen, Chiang, & Storey, 2012; Elragal & Haddara, 2014). This data-analytic thinking promotion and enhancement to the decision-making process is the basis for creating a *data-driven decision-making* ecosystem, as depicted in Figure 1. Data-driven decision making (DDD) refers to the practice and tradition within enterprises of grounding their decisions on the results of their data analysis, rather than purely on intuition, tribal knowledge, and gut feeling (Brynjolfsson, Hitt, & Kim, 2011; Provost & Fawcett, 2013). For example, procurement specialists could create and estimate their budgets and spend forecasting based solely on their long experience in the field and

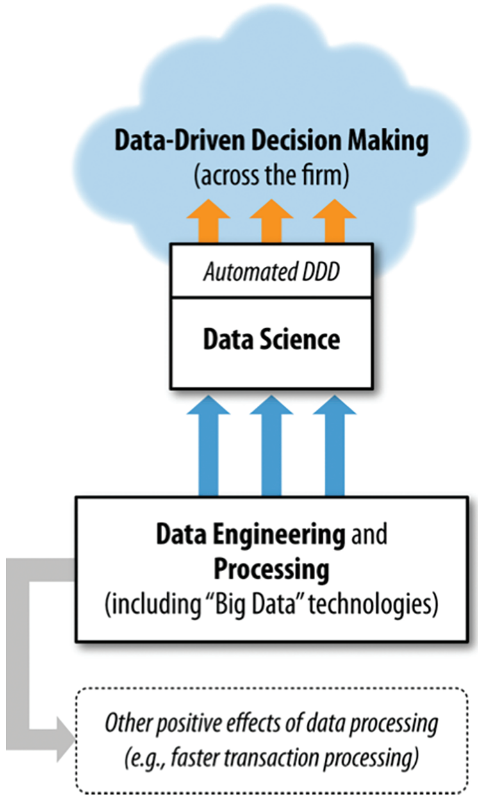

Figure 1. The DDD ecosystem (Provost & Fawcett, 2013)

intuition. Or they could base their spend planning on the analysis of data related to their procurement spend data and its impact on profitability. Another alternative for procurement specialists could be to use a blend of these two approaches (Provost & Fawcett, 2013), as DDD is not an all-or-nothing practice, and different enterprises engage in DDD to greater and lesser degrees (Haddara & Larsson, 2017). DDD is not considered as hype or a buzzword; in fact, the benefits of DDD have been demonstrated and documented in academia and industry alike. For example, several comprehensive studies (such as Brynjolfsson et al., 2011; McAfee et al., 2012) have presented their findings showing how DDD is positively correlated with, or positively affects, enterprise performance.

The domain in focus in this research is the adoption of data analytics and DDD in public procurement in Norway, which is widely known as *procurement analytics.* Public procurement is considered as one of the four major economic activities governments engage in (Thai, 2001). In addition, data-driven procurement is a term used to describe a procurement strategy that makes data central to its processes and then utilizes insights derived from this data to drive the decision-making process. Exploring the decision-making process in public procurement is highly critical since the procurement activities conducted by governments account for a substantial portion of the European economy. According to the European Commission (2017), governments in the European Union (EU) spent 13.5 % of their GDP (€2 trillion) on services, goods, and supplies in 2017. In Norway alone, the government spent NOK 564 billion in 2018 (Statistics Norway, 2020). Given the massive expenditure on the line, the Norwegian Government, as well as international organizations like the EU, the Organisation for Economic Co-operation and Development (OECD) and the World Trade Organization (WTO), are increasingly anxious to secure better value for money and to reduce the burden on the often-strained public budget. To improve procurement effectiveness, the European Commission's strategy on public procurement (2017) recommends the application and employment of data-driven decisions, stating: "Improved and more accessible data on public procurement will make it possible to better assess the performance of procurement policies, optimize the interaction between public procurement systems, and shape future strategic decisions." DDD is also a strategy that is supported by the OECD and the Norwegian Government (van Ooijen et al., 2019). Brynjolfsson et al. (2011) argue that firms that adopt DDD show a 5–6 % higher output and productivity than others. In a ranking of national technology strength by *Global Finance* (Getzoff, 2020), Norway was ranked number one based on the availability and prevalence of technology. According to the *National Strategy for Artificial Intelligence* (Ministry of Local Government and Modernisation, 2020), the public sector in Norway is more technologically advanced and digitalized than most other countries. Thus, Norway has a highly functioning and efficient public sector. There are, nevertheless, major challenges, and the main ones are related to the operation of public procurement in a decentralized manner and the systematic collection and utilization of public procurement data. Capacity (both in terms of quantity and skills) plays an important role in this context as well. For example, smaller contracting entities, either at central level or on the periphery of the national system, struggle with human resources and capacity issues (Meld. St. 22 (2018–2019)).

Despite its substantive impact on the Norwegian economy, public procurement, in general, has not been a popular area of research. A review by Lange et al. (2014) showed that only 18 articles focusing on Norwegian public procurement were published between 1997 and 2012, and none of these articles explored the adoption of analytics. According to a Norwegian white paper on public procurement (Meld. St. 22 (2018–2019)), government leaders do not take advantage of the potential of data for decision-making in procurement. The white paper recommends that purchasing management should enable the DDD environment to enhance both the way decisions are made and the impact of those decisions. While the emergence of new technologies has created a vast amount of data, including procurement data, you may find that in a typical public procurement organization today that the data is spread across several databases and data warehouses, as well as a jungle of informal SharePoint folders and Excel repositories. This makes it difficult for procurement organizations to exploit the opportunities hidden in the data. Hence, in this research, we aim to explore the current status of DDD and data analytics adoption within the public procurement domain in general, and their application within the public procurement processes in particular.

The main research question we can deduct from the previous discussion is: *"What is the status of data-driven decision-making and data analytics adoption in public procurement in Norway?"*

The rest of this research is organized as follows: in the next section, we provide a literature background for this study. In Section 3, we present the research design and methodology adopted in this study. The main findings are presented in Section 4, followed by a discussion in Section 5. Finally, a conclusion is provided in Section 6.

2 Study background

Since the ground-breaking invention of Gutenberg's printing press in the fifteenth century, our information and data stock has doubled every 50 years. Currently, the momentum, velocity, and pace of data generation are increasing drastically. According to the management consulting firm McKinsey and Company, data volume is amassing annually at a rate of approximately 50 % (Manyika et al., 2011).

At present, enterprises are acquiring and storing as much data as possible as enterprises chiefly believe that they can attain a competitive advantage, increased return on investments (ROI), and valuable insights from this data (Haddara & Larsson, 2017). In other words, if data has the potential to be valuable, and storage costs are decreasing, why not collect and store this potentially rich data for data science and analytics purposes? (Dhar, 2013). The data science domain and projects employ computer science, data mining, statistics, visualizations, and human-computer interaction techniques and approaches to analyze data to create data products and empower DDD within organizations (Dhar, 2013). Hence, the fundamental concepts of data science and analytics are drawn from various disciplines, which are essential for deriving useful knowledge and insights from data to solve business problems and enhance the decision-making process (Haddara & Larsson, 2017). In general, data science projects either apply exploratory data analysis techniques to generate hypotheses or seek predictions based on predictive techniques such as regression and classification in an explorative manner (Elragal & Haddara, 2019). The latter techniques are the most popular in the big data domain. Data science research and projects principally follow a clear set of stages or frameworks, see Figure 2 for an abstract example of the data science process. Data science related information systems (IS) are characteristically highly distributed and scalable in order to handle the enormous datasets found in modern enterprises. Data processing and manipulation in data science and analytics environments include creation, retrieval, storage, analysis, presentation, visualization, and any other activity that is typical for an information system to be used to enable the DDD process (Schelén et al., 2015).

In their paper, Brynjolfsson et al. (2011) introduced a measure that ranks and rates enterprises based on how strongly they use data to make decisions across the company. Their statistical results show that the more data-driven an enterprise is, the more productive it is, even controlling for a wide range of possible confounding factors (Provost & Fawcett, 2013). In addition, the study also demonstrates that DDD is positively correlated with a higher return on assets and equity, greater asset utilization, and higher market value, and the relationship seems to be causal (Brynjolfsson et al., 2011; Provost & Fawcett, 2013). Similarly, another study by Cao and Duan (2014) argues that the data-driven culture in organizations is an essential factor that gives them a competitive advantage. Thus, DDD, data science and data analytics approaches have been adopted and applied in various industries to help formulate business strategies and enhance the decision-making process and are considered among the most critical management developments in business practices (Haddara et al., 2018; Vasarhelyi et al., 2015). While exponential data growth is providing a lot of potential opportunities for organizations, the scarcity of data science and analytics skills is leaving most organizations with serious blind spots (Berman & Korsten, 2013). Studies have proven that DDD can affect organizational performance; however, many organizations are still not implementing it. A survey conducted by IBM found that one out of three business leaders admit to repeatedly making decisions with no data to back them up (Berman & Korsten, 2013). This was also confirmed in a study conducted by Accenture in 2014, which found that 97 % of senior executives understood how data analytics could benefit their businesses, but only 17 % implemented it in practice (Pearson et al., 2014).

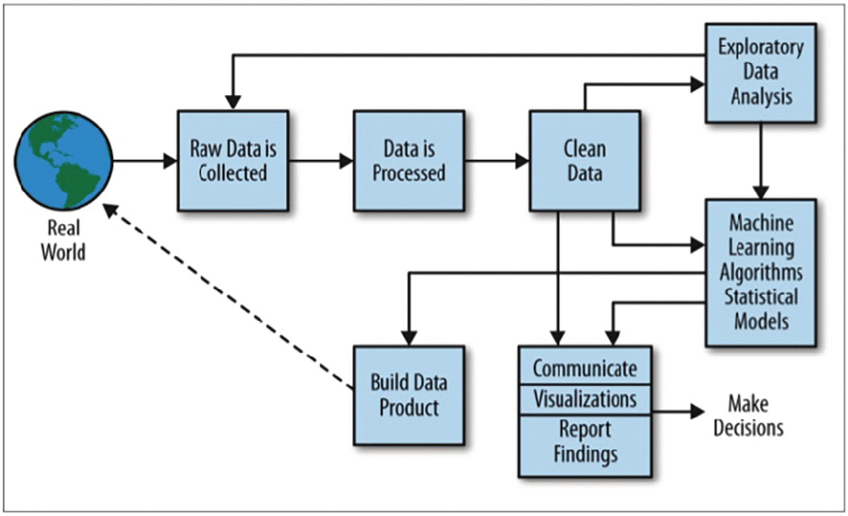

Figure 2. Data science process (Schutt & O'Neil, 2014)

Figure 2 above illustrates the different phases of data science initiatives projects will face throughout the analysis process. In the first phase, the data collection from the different data sources occurs, followed by data processing, in which the data scientist cleanses the collected data. The data processing/cleansing phase includes data manipulation and treatment of data errors. Data errors are diverse; some common examples include missing values, redundancy, and data range problems. After the data cleansing process is complete, the data is now ready for analysis, and the scientist will start exploring the data and look for any trends or patterns that could later yield new knowledge and insights for the respective domain. In the next phase, data modeling and in-depth data analysis occur. It is common at this stage for the analyst to run and combine several techniques on the dataset, which is usually referred to as the ensemble of algorithms. After obtaining results from the analysis, the scientist will communicate the results of the analysis in a way that would be useful to the target user and decision-maker. In the final stage, the results can be turned into data products for reusability. Data products turn the data assets a company already owns or can collect into a product designed to help a user solve a specific problem (Haddara & Larsson, 2017). Some examples of data products are recommender systems, search ranking algorithms, supplier ranking algorithms, supply chain route optimization, and bottleneck detection algorithms.

In the context of procurement, data analytics for procurement is commonly referred to as *procurement analytics*. According to Westerski et al. (2015), procurement analytics is the adoption of techniques and technologies within the framework of procurement performance optimization. Very few studies have explored the potential application of data science and analytics for procurement agencies. For example, Handfield et al. (2019) argue that there is currently a low usage and adoption of advanced procurement analytics in organizations worldwide. Their findings suggest that data integrity problems and quality-related issues might be hindering the advancement in procurement analytics (Handfield et al., 2019). Thus, the authors argue that there is a paramount need for enterprises to establish coherent protocols and approaches for the collection and storage of trusted organizational data, which are based on internal sources of spend analysis and contract databases. In addition, their findings suggest that promoting the DDD culture within organizations is essential to pave the way for procurement analytics (Handfield et al., 2019). Likewise, several other studies highlighted the importance of spreading the analytical thinking and DDD cultures within enterprises (Brynjolfsson et al., 2011; Cao & Duan, 2014; Haddara & Larsson, 2017; McAfee et al., 2012; Schutt & O'Neil, 2014). Figure 3 demonstrates the different organizational levels and attitudes towards data usage in decision-making and illustrates the general motivations for adopting data-driven initiatives in enterprises. Other studies have argued that data analytics adoption within organizations can enhance the procurement process in general and help in detecting fraudulent procurement practices and transactions (Ramamoorti & Curtis, 2003; Tan & Lee, 2015). Another study, conducted on governmental purchasing data in Singapore, argues that algorithms to predict future purchasing of goods and services by public agencies have the potential to enhance the budget and spending estimations (Westerski et al., 2015).

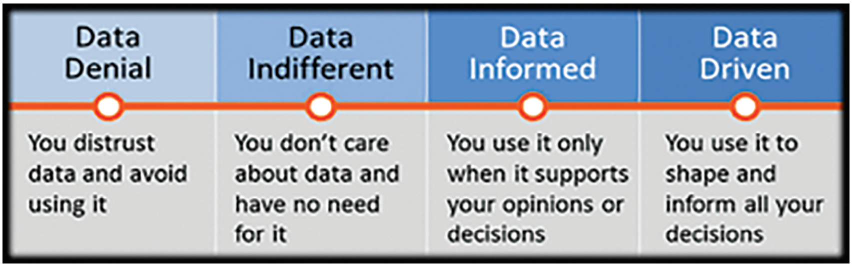

Figure 3. The degrees of data incorporation in decision-making (Kushinka, 2019)

As mentioned earlier, the overall aim of this research is to explore how data analytics is adopted by organizations and practitioners for DDD within the public procurement domain in Norway. Moretto et al. (2017) argue that data-driven decisions have been thoroughly investigated in marketing and sales, and although some authors have also discussed their relevance to procurement, the literature on this topic remains scarce. LaValle et al. (2011) argue that data is a source of power that remains useless if it is not properly exploited. Similarly, several studies argue that management promotion and embracing of DDD culture in public organizations may increase the citizens' trust in governmental practices and decisions (van Ooijen et al., 2019), achieve sustainability objectives and promote DDD among employees (Gelderman et al., 2015), and eventually enhance service quality (Manikam et al., 2019). Several papers have deemed that the digital transformation of public agencies and types of digital tools used by employees affects the organizational readiness to embrace data science and analytics, enabling a step forward towards data-driven cultures (da Rosa & de Almeida, 2018; Gong, et al., 2020; Han et al., 2020; Merhi & Bregu, 2020; Reis et al., 2018; Seres et al., 2018). Others have stressed the importance of enhancing employees' competence in regard to data science, analytical thinking, and data analytics (Mentsiev et al., 2020; van Ooijen et al., 2019; Veale & Brass, 2019). Another study (Shahbaz et al., 2019) in the Pakistani healthcare sector investigated the effect of the individual employee's task-technology fit as a predictor for data analytics adoption. The study findings suggest that the greater the fit between the technology and the task, the more likely it is that employees will adopt data analytics. Another important factor for investments in information systems and ICT in general, and in analytics and data science projects in particular, is the budget size of the organization (Haddara et al., 2018).

Based on our literature review, we can summarize that there are five main factors that affect the adoption of data science, analytics, and DDD in public organizations, as shown in Figure 5 below. These are: 1) The degree of use of digital tools and organizational readiness; 2) the employee competence and skills in analytics; 3) the budget size; 4) the leadership involvement and promotion of DDD culture within their respective organizations; and finally, 5) national policies and technology availability.

3 Theoretical framework

Various theoretical models and frameworks have been used as lenses to investigate and study organizations' adoption of IS/IT innovations and technologies in general, and data science and analytics in particular. Some of the widely used theoretical models in IS research include the classical Technology Acceptance Model (TAM) (Davis, 1985); the Theory of Planned Behavior (TPB) (Ajzen, 2002), Diffusion of Innovations (DOI) (Rogers, 2010), and the Technology-Organization-Environment framework (TOE) (Tornatzky et al., 1990). Where the TAM and TPB frameworks are aimed at the individual level, DOI and TOE are better suited for studies that target the enterprise level, as most studies on IT adoption at the firm level are derived from theories such as the latter two (Chong et al., 2009). Our study focuses on the wider context of an enterprise, and thus two theories/frameworks were initially deemed as potential candidates for this research, namely DOI and TOE. Based on the five adoption factors we identified in our review of literature, we sought after the TOE framework, because it has a socio-technical dimension and includes the technological (for example, use of digital tools), organizational (for example, skills, budgets, leadership involvement, and culture) and environmental (availability or absence of technology, national policies) contexts that cover our identified factors. Hence, we consider the TOE framework (Figure 4) as more suitable and relevant for explaining data science and analytics adoption for procurement in public enterprises, especially for reflecting the contextual importance.

3.1 Technology-Organization-Environment framework

As this is exploratory and highly contextual research, the TOE framework (Tornatzky et al., 1990) was reckoned beneficial, as it can explicate how the organizational context influences the adoption and implementation of technologies and innovations. In addition, the TOE framework has been employed in earlier studies investigating data analytics adoptions in private enterprises (for example, Maroufkhani et al., 2020; Olufemi, 2019), and in public organizations (for example, Ijab et al., 2019; Maroufkhani et al., 2020).

The TOE framework features three general aspects of an enterprise's context that may influence the adoption and implementation of the technological innovation process: the *technological* context, the *organizational* context, and the *environmental* context. The three dimensions are also consistent with the innovation diffusion theory, which highlights technological characteristics, and both the internal and external characteristics of organizations as drivers for technology diffusion (Rogers, 2010).

Briefly, the *technological* aspect refers to the set of technologies that the enterprise is currently using and their characteristics, as well as the availability of other technologies not in use by the enterprise. A firm's existing technologies (for example, digital tools) and infrastructures are important in the adoption process because they set a broad limit on the scope and pace of technological change that an enterprise can embark on (Baker, 2012). *The organizational* aspect denotes the characteristics and resources of an organization, including linking structures between employees, intra-firm communication processes, top-management involvement and support, (analytics) culture, enterprise size and budget,

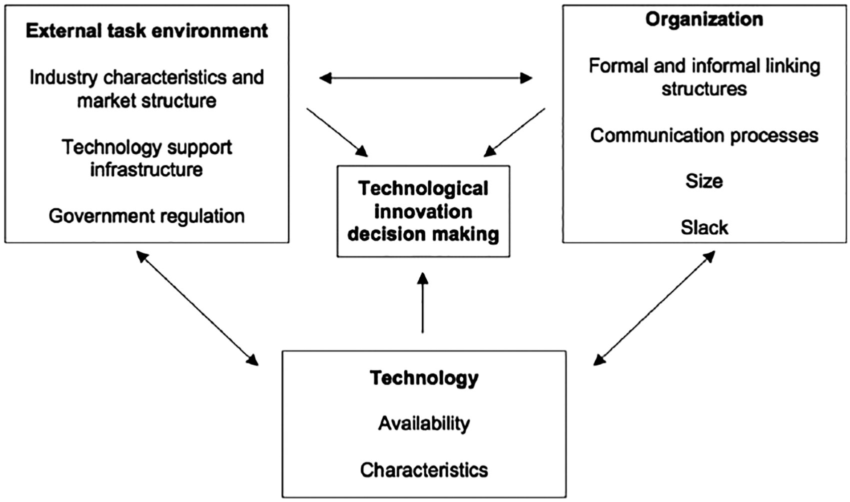

Figure 4. The TOE framework (Tornatzky et al., 1990)

and the number of resources and skills (Sædberg & Haddara, 2016). And finally, the *environmental* aspect includes the structure of the industry, the national presence or absence of technology service providers, the national policies and regulatory environment, and public funding (Baker, 2012). For this study, the TOE framework has been adopted to identify technological, organizational, and environmental factors relevant to data science and analytics adoptions for public sector organizations. The TOE framework has also been used in scoping the data collection process from the survey, and as a basis for our data analysis. As mentioned earlier, the factors identified in this research are based on what the extant literature identified as determinants for analytics adoption in enterprises.

3.2 Hypotheses

Based on our literature review and the framework discussed in this research, the following hypotheses were developed regarding the survey results.

- **H1a:** Organizational factors such as budget size are positively correlated with the degree of adoption rate/deployment of data science and analytics in public organizations.

- **H1b:** Organizational factors such as leadership involvement and promotion of DDD have a positive impact on analytics adoption.
- **H1c:** Organizational factors such as employee competence in analytics have a positive impact on analytics adoption.
- **H2:** The technological context such as the use of digital tools and organizational readiness has a positive impact on analytics' adoption.
- **H3:** The environmental context such as the national policies and technology availability has a positive impact on the enterprise adoption of data science and analytics technologies.

4 Research methodology

This research explores the status of adoption of data analytics for supporting public procurement activities in Norway. In particular, we focus on the adoption of analytics for public procurement processes and the research hypotheses provided above. Below is a brief description and overview of the research design, data collection methods, sample, and the data analysis.

4.1 Research design

An exploratory data analysis and a descriptive design were adopted and employed in the study. Descriptive statistics is used to describe the basic features of the data in a study (Shreffler & Huecker, 2020). The key source of data for the study was secondary data from a survey conducted by the Norwegian Agency for Public Management and eGovernment (Difi) in 2018. Secondary data is defined as quantitative or qualitative data that has been collected by someone other than the researcher(s) (Yin, 2009). The study attempts to identify factors that influence data analytics adoption within public procurement in Norway. As discussed earlier, the authors have derived five main factors that may affect the adoption of data science and analytics techniques in public organizations. Thus, the factors of degree of use of digital tools, employee skills and competence, budget size, leadership involvement and promotion of DDD culture, and the national policies and technological infrastructure are the independent variables, while data analytics adoption is the dependent variable in this study (see Fig. 5).

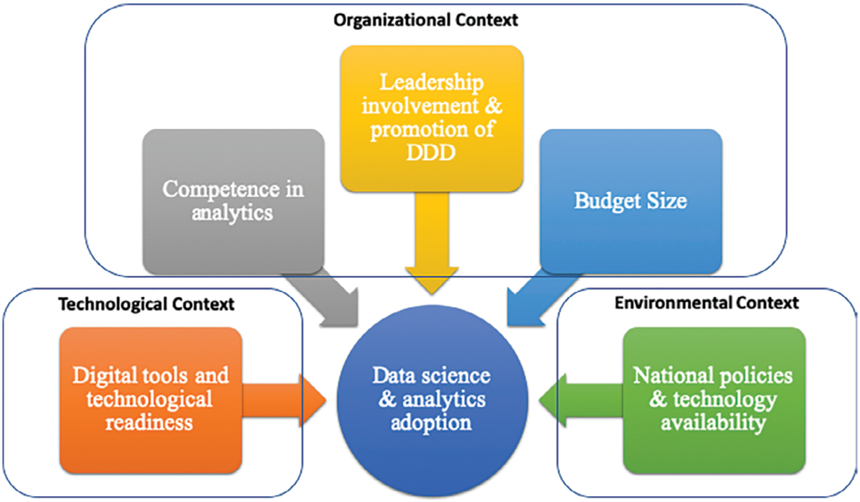

Figure 5. TOE factors affecting data science and analytics adoption in public organizations

4.2 Data collection

Rambøll Management Consulting conducted a survey on behalf of the Norwegian Agency for Public Management and eGovernment (Difi) aimed at purchasing managers in state enterprises, counties, and municipalities. The purpose was to form a knowledge base on how procurements are organized and carried out in the public sector in general, and digital maturity related to procurement in particular, as well as the maturity among public buyers related to setting requirements for environmental and social responsibility in public procurement. The survey was divided into three parts. One section dealt with maturity in procurement in general, and two in-depth sections addressed digital procurement and green procurements, respectively. We focused on the section of procurement in general and the section that addressed digital procurement.

In total, the two sections in the survey consisted of 259 questions with a five-points Likert scale (Awang et al., 2016). The general survey was divided into six main areas: (1) cooperation and process, (2) management and leadership, (3) competence and capacity, (4) sustainability, (5) innovation, and (6) digitization and technology. While the survey addressed different topics, in this study we have chosen to focus solely on the ten questions in the survey that were related to the use of analytics, employee competence, use of digital tools, and leadership involvement in regard to decision-making. These questions focused on whether respondents do analysis on spend, risk and the market, how they evaluate their own analytical skills, and whether they report numbers to top management. Thus, the descriptive statistics from the survey are the employees, and the survey attempts to provide both an overview of the current state of the adoption of analytics and evaluate how widespread their use is in Norwegian public procurement agencies.

4.3 Response rate

The survey was sent out to 888 respondents, of whom 343 replied. Hence, the survey has a response rate of 38.5%. An overview of respondents and their organizations is provided in the table below.

Table 1. Overview of respondents

	State enterprises		Counties		Municipalities		Municipal and state companies	
	Number	**Share**	**Number**	**Share**	**Number**	**Share**	**Number**	**Share**
Respondents	115	33%	11	3%	136	40%*	81	24%

*Several municipalities are part of a purchasing cooperation and have refrained from answering the survey; however, they have allowed their purchasing representative to respond on their behalf. These are not counted in the total. Of the municipalities that have not responded, 220 have less than 10,000 inhabitants.

4.4 Data processing and analysis

There are three main objectives in data analysis: getting a feel for the data, testing the reliability of the data, and answering the research questions (Heeringa et al., 2017; Yin, 2009). Establishing the reliability of data lends credibility to all subsequent analysis and findings, as it measures the reliability and the validity of the measures used in the study. After gathering data from the questionnaire responses, it was checked for reliability and further clarification by doing data preparation in steps, in which records with missing values were excluded before conducting further analysis. The data was then analyzed using a quantitative technique, Correlation Analysis. The attribute "use of analytics" was used as the dependent variable. The authors used Excel to conduct some data preparation tasks and RapidMiner for the statistical analysis.

5 Main findings

As discussed earlier, five main factors were identified in the literature that could potentially affect the adoption and use of data science and analytics within public organizations. Hence, our findings below are organized and presented according to these factors in relation to whether data science and analytics are employed within organizations.

5.1 Budget size

Budget size refers to the size of an organization's procurement budgets (investments and operations).

Below, we combine the results of two separate questions, revealing the budget size and the degree of employment of analytics for public procurement in those organizations. Our descriptive results indicate that the organizations that have smaller procurement budgets do less analytics than the ones with larger procurement budgets. Hence, the results suggest that the larger organizations have more resources to cover the cost of analytics and have a greater tendency to do analytics, as presented in the figure below. While the descriptive results suggest that there is a positive correlation between budget size and the use of data analytics, our correlation test result (in Fig. 6) does not support this contention.

Q: How large is the organization's total procurement budget for goods and services in relation to their use of analytics in their procurement planning?

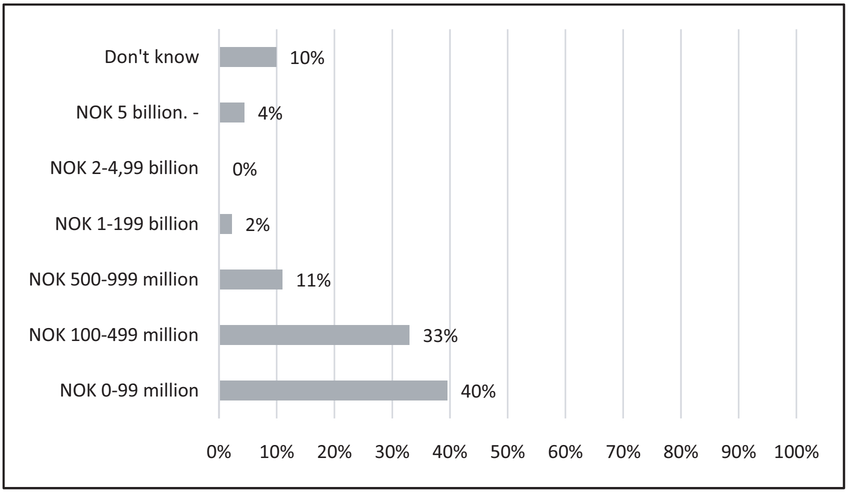

Figure 6. Budget comparison and degree of analytics adoption in percentages

Use of analytics	Budget size	0.081

Figure 7. Correlation results: budget size and use of analytics

5.2 Use of digital tools in the procurement process

As presented in the literature review, the better the technological infrastructure, the greater the likelihood of data analytics adoption (Lai et al., 2018; Verma & Chaurasia, 2019). Consequently, Gangwar (2018) argues that the technological advancement of public organizations in India is considered to be a predictor of their data analytics adoption. Further supporting this, digital technologies are increasingly being used to support the execution of all aspects of the procurement process in the Norwegian public sector. From the results, we see that 80–90% of the respondents use digital tools to receive invoices, announce calls for tenders, and receive offers. However, only 34% use digital tools for purchasing planning, and less than half (42%) use digital tools for evaluating offers, as depicted in Figure 8.

Q: To what extent do you use digital tools in the procurement process?

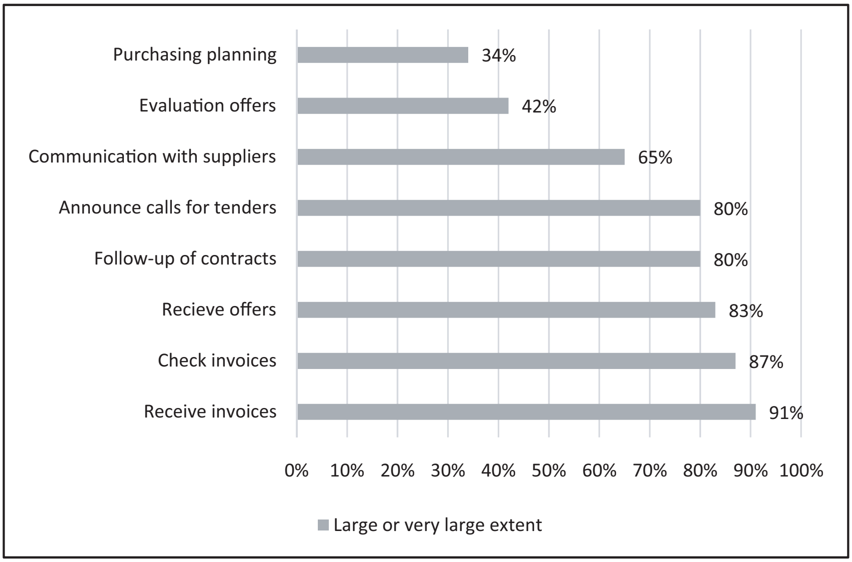

Figure 8. An overview of the use of digital tools for the various procurement processes

Our descriptive results suggest that the degree of digital tools usage in organizations has no strong impact on the adoption and use of data science and analytics within those organizations. This has also been confirmed with our correlation test shown in Figure 10. The next question was formed as an assertion: *We do not do any surveys and analyses in connection with planning of our procurement portfolio.*

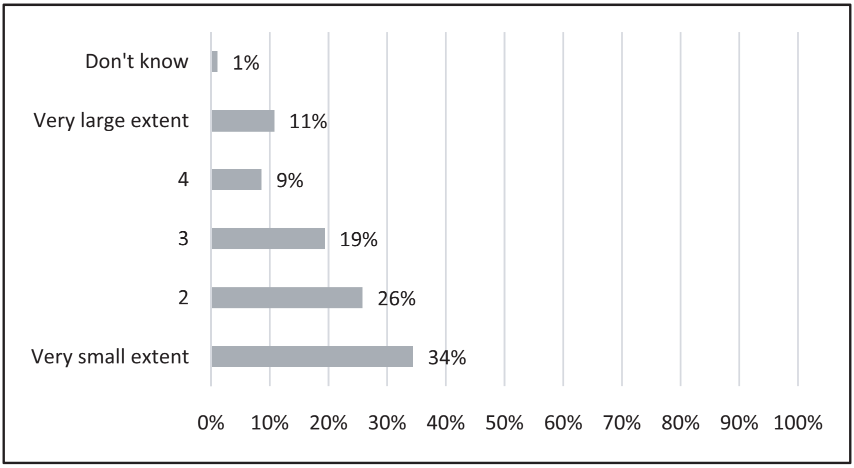

Figure 9. An overview of the use of digital tools in the planning process of procurement

Use of analytics	Use of digital tools	–0.009

Figure 10. Correlation analysis results: Use of analytics and Use of digital tools

5.3 Competence in analytics

Analytical and data science competence requires deep domain knowledge and a broad ensemble of analytical skills. Analytical competence refers to the ability to conduct data analytics, such as spend analysis. For employees to develop a broad set of analytical skills, they require training and consistent investment of their time. Developing deep domain knowledge also requires a parallel dedication of effort (Waller & Fawcett, 2013). Besides having theoretical knowledge of analytical methods and techniques, the data scientist should be inventive and able to identify business solutions using IT. Moreover, the data scientist and data analyst should have strong domain knowledge and the ability to communicate the results to the various stakeholders (van der Aalst, 2014). In addition, many studies argue that the higher the employees' competence is in analytics, the more likely they are to employ analytics in their work. Likewise, our descriptive findings suggest that organizations that have analytical competence do more analytics in their procurement planning, as shown in Figure 12. However, this result was not supported in our correlation test results, as shown in Figure 13. Figure 10 demonstrates the general percentage of employee competence in analytics within organizations.

Lack of competence is clearly a major challenge for digital development in the public sector. Forty-three percent of the respondent's state that they lack competence in analytics to some extent or to a great extent. In order to implement data science and analytics projects successfully, skilled professionals and data analysts are needed. Therefore, the benefits of leveraging on analytics will be limited due to the shortage of skills and experience of employees. The problem of skill shortage is believed to be greater in the public sector compared to the private sector, as private-sector employers usually pay more to attract skilled professionals.

Q: To what extent do you find that your business has sufficient purchasing expertise in analytics in general (spend analyses, market analyses, supplier analyses, demand analyses, etc.)?

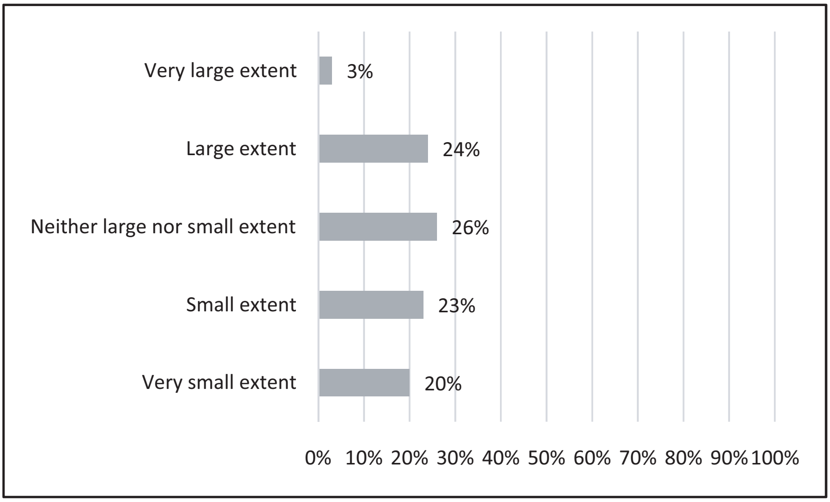

Figure 11. Degree of competence in data analytics

Q: To what extent do you find that your organisation has sufficient competence in procurment analytics (spend analyses, market analyses, supplier analyses, demand analyses, etc.) in relation to whether the organisation adopts analytics in planning its procurement?

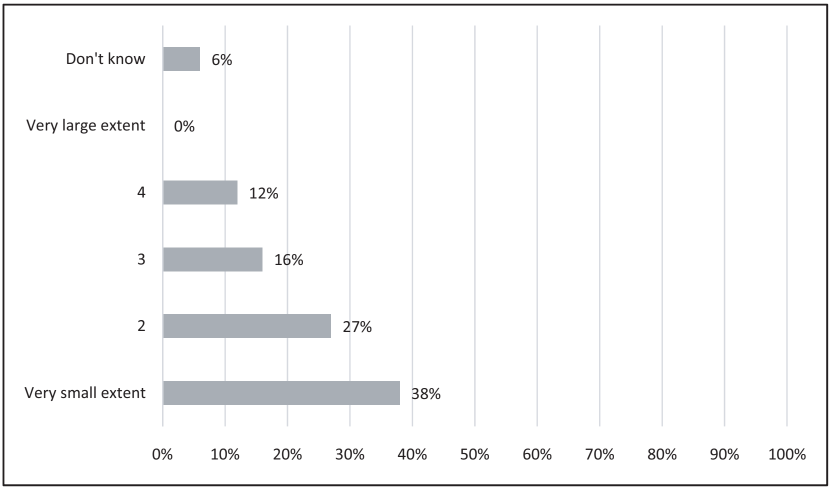

Figure 12. Degree of competence in analytics and degree of analytics adoption in percentages

Competence in analytics	Use of analytics	–0.020

Figure 13. Correlation analysis: Competence in analytics and use of analytics

5.4 Leadership involvement and promotion of DDD culture

Leadership involvement or, as it is also known, *top-management support,* has been recognized in the extant literature as a major critical success factor in information systems adoptions in general (Haddara & Moen, 2017), and in the Norwegian public sector in particular (Sædberg & Haddara, 2016). When it comes to the adoption of data analytics in enterprises, Lai et al. (2018) have identified top-management support to be one of the top determinants and predictors for data analytics' adoption projects. Similarly, Gangwar (2018) argues that top-management support is critical for data analytics adoption because it can address and resolve challenges related to the promotion of the DDD culture: organizational alignment, change management, business process reengineering, coordination, and internal communication activities. Hence, one of the most critical aspects of data science and analytics is the support of data-analytic thinking and DDD culture (Provost & Fawcett, 2013). The employees' DDD skills are important, not just for data scientists but for the whole organization, even if they only have some basic understanding of the fundamental principles (Provost & Fawcett, 2013). One method to indicate the importance of DDD culture to employees is for top management to request measurable indicators and reports from their subordinates.

Procurement is often perceived as a tactical rather than a strategic function. The lack of leadership involvement is a major obstacle to better procurement decision-making. Procurement metrics provide organizations with quantifiable values to measure performance and guide procurement strategies. As shown below, 56% of our respondent's state that their leaders seldom or never ask for measurable indicators in procurement. This is surprising, given that procurement often account for over 30% of public budgets.

Q: How often are results requested on measurable indicators of the procurement area by company management?

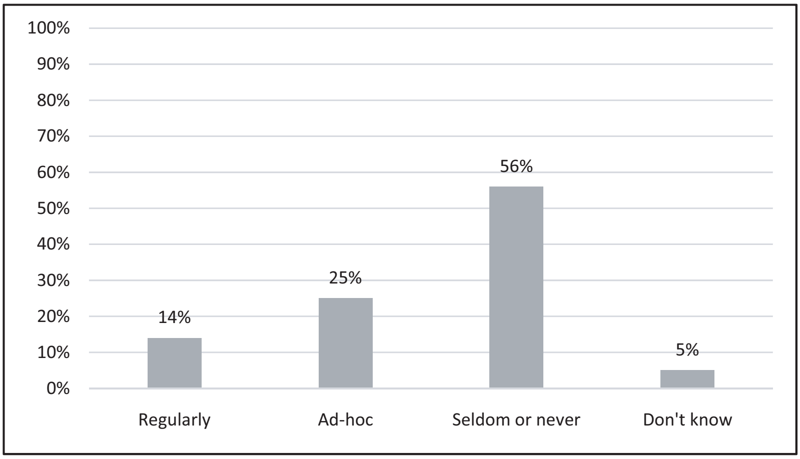

Figure 14. Degree of top-management requests for measurable indicators

Our descriptive findings suggest that in organizations where top management regularly ask for measurable indicators, they subsequently do more analytics and benefit from DDD culture (see Figure 15 below). However, our correlation analysis results indicate that there is no correlation between top-management requests for measurable indicators and the actual use and adoption of analytics in procurement (Figure 17).

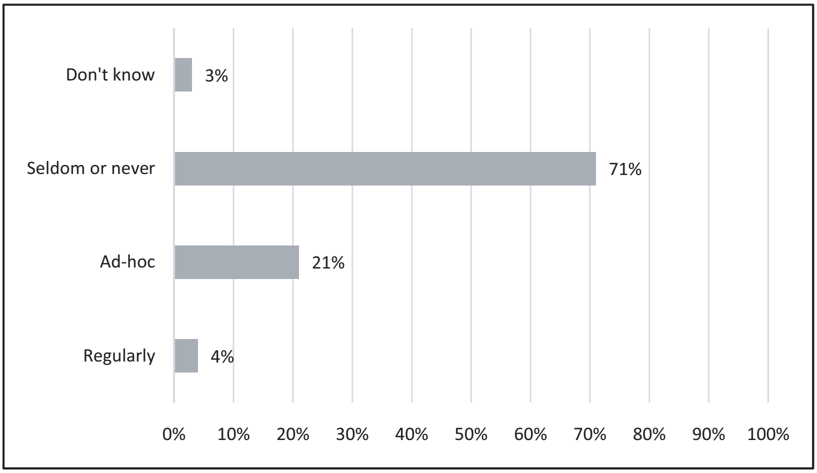

Figure 15. Degree of top-management requests for measurable indicators, seen in relation to the number of surveys and analyses carried out when planning your procurement portfolio

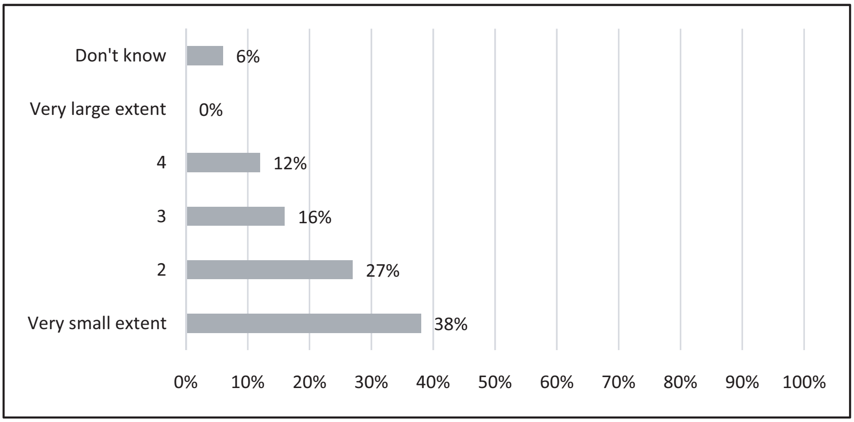

Figure 16. Degree of data analytics use for procurement planning in relation to top-management support

Use of analytics	Leadership involvement	–0.175

Figure 17. Correlation analysis: Leadership involvement and use of analytics

5.5 National policies and technology availability

As discussed in the literature review section, the Norwegian Government and the Storting (Norwegian Parliament) advocate the application of data-analytics technologies and the promotion of DDD culture in the public sector. This is in line with the EU, OECD, and the World Trade Organization's recommendations, roadmaps and visions (van Ooijen et al., 2019). When it comes to technology availability at national level, Norway is ranked number one in Europe, based on the availability and prevalence of technology (Getzoff, 2020). According to the *National Strategy for Artificial Intelligence* (Ministry of Local Government and Modernisation, 2020) the Norwegian public sector is more technologically advanced and digitalized than many other countries around the world. Thus, the public sector in Norway is regarded as highly efficient and technologically advanced. Nevertheless, while the national technological level is regarded as highly advanced in Norway, our data suggests that, currently, less than 20% of the public sector organizations in our sample employ analytics in their substantial procurement processes.

5.5.1 Hypothesis results

Based on our correlation analysis, we present our hypothesis testing results as follows:

- **H1a:** Organizational factors such as budget size are positively correlated with the degree of adoption rate/deployment of data science and analytics in public organizations. **Not supported.**
- **H1b:** Organizational factors such as leadership involvement and promotion of DDD have a positive impact on analytics adoption. **Not supported.**
- **H1c:** Organizational factors such as employee competence in analytics have a positive impact on analytics adoption. **Not supported.**
- **H2:** The technological context such as the use of digital tools and organizational readiness has a positive impact on analytics adoption. **Not supported.**
- **H3:** The environmental context such as the national policies and technology availability has a positive impact on the enterprise adoption of data science and analytics technologies. **Not supported.**

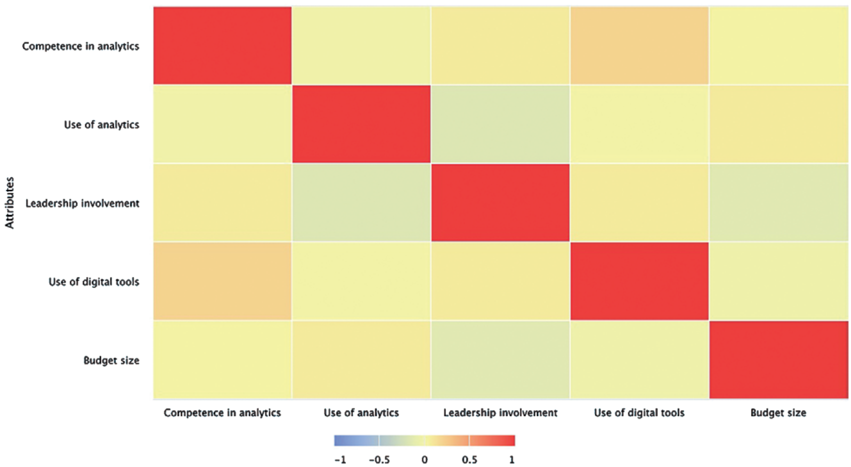

Figure 18. Correlation analysis results: Heat map

6 Discussion

Procurement analytics is the process of collecting and analyzing procurement data to form meaningful insights and aid effective business decision-making. This typically involves collecting data from several different source systems, classifying data to standard or use-case-specific taxonomies, and displaying data in a visualization dashboard or within data analytics tools.

One way to think about procurement analytics is to compare it to refining oil. It is about collecting, cleansing and enriching large amounts of data from disparate systems to create business value. In procurement analytics, value comes from more timely, accurate and actionable insights, and the ability to measure procurement's contribution to the enterprise. Public procurement organizations can utilize analytics to describe, predict or improve public sector performance. When utilized effectively, procurement analytics can enable DDD, where purchasing decisions and supplier relationships are managed more effectively. Although the need for adaption varies between use cases, the most important thing for every organization to possess is the will to adapt. Decision-makers need to accept that there will be challenges to overcome, and mistakes made and learned from. In other words, when adapting to analytics, it also involves a new way of working.

Our main descriptive results indicate that budget size, competence and leadership involvement all have a direct effect on a firm's adoption of data analytics. However, in contrast to current literature, the use of digital tools and organizational readiness have no clear impact on data analytics adoption in organizations.

Of the 343 who answered the questions regarding the use of data analytics for decision-making, 91 respondents (26.5%) replied that they do not apply data analytics at all in the planning of their purchases. Of these 91 respondents, 36 had an organizational purchasing budget between NOK 0–99 million, 30 had a purchasing budget between NOK 100–499 million, 10 respondents had a budget between NOK 100–999 million, 2 respondents had a purchasing budget of between NOK 1–1.99 billion, no respondents had a purchasing budget between NOK 2–5 billion, 4 respondents had a purchasing budget equal to or more than NOK 5 billion, and 9 respondents answered that they did not know.

A large amount of data in procurement is generated from various sources and/or applications through spending, supplier performance assessments, and negotiation, whether internal or external. These data sources facilitate the use of analytics. Even when the procurement practitioners use digital technologies in the procurement process, they do not always exploit the data that these systems provide. Only 17% analyze their spend. Spend analytics is one of the key tools that procurement organizations use to proactively identify savings opportunities, manage risks, and optimize their organization's buying power. It is often regarded as the fundamental foundation of sourcing. Eighteen percent have developed measurable indicators of their procurement practice. Given that running a data-driven business is widely acclaimed in the business community, it may come as a surprise that so few have fully realized a completely data-driven model in the public sector. It is not because public companies do not have data. They simply do not understand all the implications of the data they have.

This is not surprising, considering the high volume of complex data that technologies pump out. When it comes to employee skills, the accelerating pace of change means skill sets can rapidly become obsolete. Instead of hiring the most qualified person for a specific task, it is worth focusing on a candidate's ability to adapt to new situations in a future where humans will need to collaborate with machines to be successful in their roles. Most important in tackling the challenges of data analytics is data education, as well as ongoing training and development. On the one hand, decision-makers need to have the necessary data literacy to make informed and actionable decisions based on the data they have. Business users need to understand and evaluate their information and put it into a strategic context. On the other hand, data analysts and data scientists (as well as others heavily involved in working with data) need ongoing training to ensure that their analytical skills remain sharp and that their technical expertise grows.

Regarding leadership involvement, it seems that little has changed since Ammer (1974) wrote that "top management perception of the purchasing function is different from that of the purchasing managers themselves". While larger contracting authorities use analytics, smaller agencies do not have the skills, technical capabilities or capacity to conduct the same level of analysis. In addition, the reliability of the information in the database remains unclear: audits are carried out, but not routinely, and they remain limited to financial information.

Public sector companies adapting to analytics also need to transition to a DDD culture in order to take full advantage of it in decision-making. This culture can be nurtured by encouraging employees to challenge decisions made across all levels of the organization that are not supported by reliable data. Whether data analytics, as an emerging technology, can provide strategic, operational and other advantages across the public sector in Norway is yet to be seen based on adoption.

6.1 Limitations and further research directions

There are some limitations in this study that represent opportunities for future research. One general limitation connected to survey research is the oversimplification of social reality. The design of questionnaires and multiple-choice questions with pre-conceived categories represents an overly simple view of reality. A second important limitation with survey research is the problem related to the validity and reliability of results. The inconsistency of collected data can be attributed to the lack of accuracy or consistency in the replies given. Our research suggests several key future research areas in the interface between procurement analytics and public procurement. While the impact of data analytics on future practices is well recognized, applications of data analytics are still in question and many of them are in the developmental stage. Thus, some of the key questions for further research include: How can we develop a roadmap for data analytics in public procurement? How can we develop qualitative research to find out why government leaders do not ask for measurable indicators in public procurement? It would also be interesting to compare adoption in Norway to other European countries, and investigate how analytics can be utilized in, for example, sustainable public procurement.

7 Conclusions

Rapidly evolving technologies and the emergence of new business models are contributing to the sudden expansion in cost-reduction and growth opportunities around sourcing and procurement. Most public organizations, however, are unsure about how to transform their procurement organizations from an administrative to a strategic function that provides value to their organization.

Public procurement in Norway has an enormous impact on the economy. Norway is ranked number one in national technology strength. We wanted to explore how public procurement adopts analytics, and our main research question was: *"What is the status of data science and data analytics adoption in public procurement in Norway?"* Based on the data set, this paper shows that while the use of digital technologies in the procurement process is widespread in both state and municipalities, most of the public organizations do not utilize the massive data they store for analytics to plan or make procurement decisions.

As earlier research suggests, there seems to be a lack of competence in analytics and leadership involvement in the procurement process, which may directly affect the adoption and use of data science and analytics tools in public procurement for decision-making. Nevertheless, our analysis results are aberrant in relation to mainstream research. Our main findings suggest that budget size, leadership involvement, competence in analytics, and use of digital tools have no correlation to the actual adoption and use of data analytics in public procurement.

Focusing on public procurement, our study only scrutinizes one particular field of policy in one country of the EU. In the future, similar investigations could be conducted to evaluate the functioning of data-driven decisions in public procurement in other countries and contexts, and to test the relationships between the different variables, which may provide different results.

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