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Spend analytics in Norwegian public procurement: adoption status and influencing factors

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Abstract:
Public procurement is an essential government function representing a substantial part of a nation's economy. How decisions are made in public procurement influences nations' economic health and citizens' daily lives. In this study, we employ the technology–organization–environment (TOE) framework to investigate public procurement officials' adoption of spend analytics in Norway. Based on an analysis of survey data from 529 Norwegian procurement entities collected by the Norwegian Agency for Public and Financial Management, we find that 61% do not utilize spend analytics, with adoption rates varying across different types of entities. A correlation analysis indicates that procurement analysis competencies are significantly associated with higher adoption rates, highlighting the critical role of analytical skills. Organizational factors such as procurement volume and a centralized purchasing unit are positively linked to the use of spend analytics. Environmental factors offer a contrasting picture: while specific factors seem to drive spending analytics adoption, a strong orientation towards sustainability and competency challenges may hinder it. These findings encourage a systemic look at how the public procurement system could be more data-driven.

Keywords:
public procurement; spend analytics; data-driven decision-making; DDDM; Norway.

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1. Introduction

Public procurement is a significant economic force affecting the economic health of nations. In the European Union (EU), public procurement represents 14% of GDP, amounting to €2 trillion. According to the EU Commission [1], the public sector is expected to use public contracts strategically to achieve positive social outcomes and reduce environmental impacts. The substantial capital and the strategic functions of public procurement underscore the need for data-driven decisions to obtain an overview of where and how the money is being used. Spend analytics is defined as methods and tools that provide enterprises or countries with knowledge about how much is spent on what goods and services, who the buyers are, and who the suppliers are, thereby allowing for identifying strategic opportunities. According to the US Government Accountability Office [2], taking a strategic approach to procurement involves using spending analytics to understand better how the government is allocating its resources. In addition, the World Bank recommends using analytics in public procurement to evaluate spending [3]. The application of spend analytics is essential in strategic procurement in conjunction with the digital transformation of public procurement [4].

The digitalization of the public sector globally and in Norway is a trend that has gained momentum in public procurement [5, 6]. For several reasons, Norway represents a unique case in the study of spend analytics within public procurement. Firstly, it has a sizeable public sector with significant expenditures, amounting to €63 billion in 2022, a substantial total relative to its GDP [7]. This makes Norway an important economy for examining the impacts of procurement decisions on a national scale. Secondly, the Norwegian public sector is known for its commitment to achieving social and environmental goals through the strategic use of public contracts, as encouraged by the EU Commission, reflecting its progressive approach to procurement. Thirdly, the digitalization of Norway's public sector is aligned with global trends, thus providing a contemporary and relevant setting for investigating the role of technology in procurement practices. Lastly, despite advancements in digital capabilities, there is evidence of a lag in the adoption of data-driven decision-making in Norway's public procurement. This paradox provides a compelling backdrop for exploring the factors influencing the adoption and utilization of spend analytics, which can offer valuable insights in bridging the gap between technological potential and actual usage in a highly developed and digitally inclined public sector.

According to Pandit and Marmanis [4], spend analytics effectively achieves strategic sourcing. The shift toward data-driven approaches in public procurement is driven by the dual forces of an expanding data universe and the decreasing cost of managing data. Together, these forces drive greater efficiency and productivity in the public sector [8]. Despite clear recommendations, current research on adopting data-driven approaches and spend analytics in public procurement is limited [9]. Patrucco et al. [10] report a lack of research focusing on the use and impact of digital tools and procedures for supporting procurement activities. Langseth and Similä [11] highlight that there is a lack of empirical research precisely quantifying the impact of spend analytics on public procurement performance and emphasize that the Norwegian context is particularly underexplored, meaning that limited insight is available into how these global trends are manifested within the nation's public procurement practices.

An OECD working paper by van Ooijen et al. [12] argues that reductions in data storage and processing costs require the government to adopt data analytics and data-driven decision-making (DDDM) for evidence-led policymaking and data-backed service design [13]. The opportunities for public procurement to be more strategic are broad if a DDDM ecosystem is incorporated, as the procurement function can access data from internal transactions, suppliers, environmental footprints, and more. This wealth of data has stimulated the adoption of DDDM in other government operations, such as healthcare [14]. The drive to introduce DDDM into public procurement aims to capitalize on the benefits of big data analytics, thereby transforming public procurement into a data-driven function within the government [15]. As a paradigm, DDDM can help extract actionable insights from data and uses techniques for interpreting complex trends and patterns [16]. In a data-rich environment, the symbiosis between domain knowledge and data analysis is crucial for accommodating informed decisions [17]. Provost and Fawcett [16] have mapped out the DDDM ecosystem (see Figure 1), charting the evolution from intuitive to data-driven enterprise decision-making. Combining data analysis and experiential knowledge can lead to more informed decisions. The positive impact of

DDDM on performance has been validated across various sectors [18], thus confirming the value of a data-driven approach.

Historically, the public sector has provided limited resources for data analysis, and according to the study in [19], the limited adoption of data analytics in the public sector arises from a lack of top management and organizational support and the absence of proper information and data management [20]. Despite Norway's recognition of technological advancements and its efforts toward public sector digitalization, challenges persist in adopting data analytics in government operations. A Norwegian white paper on public procurement highlights the underuse of data in procurement decision-making and calls for an environment that encourages DDDM to improve decision-making quality [21]. The limited use of data for decision-making has also been supported by an OECD assessment of the Norwegian public procurement system [22], which states that there is a lack of monitoring systems to measure the effects of public procurement decisions.

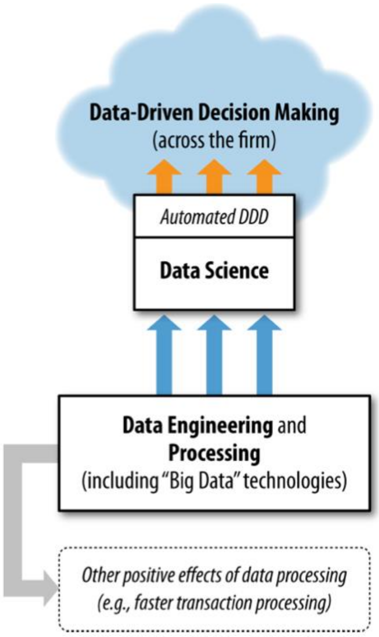

Fig. 1. The DDDM ecosystem adopted from Provost and Fawcett [16]

To address the gaps in current research, this study examines the implementation of analytics among public procurement professionals in Norway, particularly regarding spending analytics and the determinants influencing adoption. The primary research question addressed here is: *What is the status of spend analytics adoption in public procurement in Norway, and what technological, organizational, and environmental factors influence this adoption?* In addressing this question, the study also explores the interplay between technological readiness, organizational capabilities, and the external environment. By focusing on spend analytics, this study not only contributes to the academic discourse on public procurement but also provides practical insights for stakeholders in the public sector aiming to improve the adoption of analytics.

The remainder of the paper is organized as follows: in the next section, we provide an overview of related research and discuss the theoretical framework for this study. In Section 3, we present our research design and methodology. The findings are presented in Section 4, followed by a discussion of these findings, their implications, and the limitations of this research in Section 5. Finally, a conclusion is provided in Section 6.

2. Related research and theoretical background

Since the development of Gutenberg's printing press in the fifteenth century, the accumulation of information and data has increased by a factor of two every 50 years. However, in contemporary times, the rate of data generation has surged dramatically. As reported by McKinsey and Company, there is an annual growth in data volume of about 50% [23]. The continuous reductions in data storage costs further strengthen this trend towards data accumulation, making it a worthy asset for analytics pursuits [24].

2.1. Related research

In public procurement, data and spending analytics are collectively called 'procurement analytics'. Interestingly, while DDDM adoption is well researched in private sector areas such as marketing, its exploration in public procurement remains limited [25]. However, some researchers have examined its dynamics, challenges, and applications. Langseth and Haddara [26] studied the adoption of data analytics in public procurement in Norway. They highlighted the influence of organizational factors such as employee competence and top-management support on its adoption. However, they reported that none of these factors were found to have significant effects. Ghosh [27] investigated cloud-based big data analytics and emphasized the facilitating role of information technology (IT) infrastructure, internal capabilities, and vendor support. The study also identified barriers, including a lack of an analytics culture and top management support. Merhi and Bregu [28] stressed the significance of technological advancements in effectively using big data analytics in the public sector. Weng [29] investigated the relationship between business strategies and the adoption of big data analytics and found that a strategic framework heavily influenced the intention to adopt. Farshchian et al. [30] discussed the challenges facing technology adoption related to public procurement innovation. Rada et al. [31] highlighted the merits of software applications in public procurement, particularly regarding time efficiency and the adoption of big data analytics. Handfield et al. [32] raised concerns about advanced procurement analytics' low global adoption rate and pointed out data quality issues. They argued that standardized data collection protocols fostered a culture of DDDM within organizations. Other research has demonstrated the power of data analytics in streamlining procurement processes and identifying fraud [33]. Finally, LaValle et al. [34] and van Ooijen et al. [12] have emphasized the potential of DDDM in the public sector, from supporting citizen trust to enhancing service quality. A summary of the present research and the main findings is provided in Table 1.

Table 1. Summary of related research and findings

Publication	Main findings
[10]	There is a lack of research that explores the use and impact of advanced tools and procedures for supporting procurement activities.
[12]	The adoption of data analytics offers the potential for better decision-making.
[25]	There has been a limited exploration of DDDM in public procurement compared to other sectors.
[26]	Organizational factors such as employee competence and top management support of adoption have an influence, although none have significant effects.
[27]	IT infrastructure, internal capabilities, and vendor support facilitate cloud-based analytics adoption; barriers include a lack of an analytics culture and management support.
[28]	Technological advancements, data security, and transparency are vital for adopting big data analytics successfully.
[29]	Business strategies, especially strategic typologies, impact the adoption of big data analytics.
[30]	Challenges include the evolution of procurer roles, procurement methods, and collaboration, which are hurdles that impact technology adoption.
[31]	Software in public procurement offers time efficiency benefits, and the role of big data is emphasized.
[32]	The low global adoption rate of procurement analytics is due to data quality issues, the importance of standard data protocols, and Data-Driven Decision-Making culture.
[33]	Predictive algorithms enhance budgetary and spending estimates when used in public agencies.
[34]	The use of DDDM in the public sector can boost citizen trust, enhance service quality, and serve sustainability goals.

According to our literature, the adoption of spend analytics in public procurement is influenced by organizational, technological, and strategic factors. Key enablers include top management support, IT infrastructure, and standardized data protocols, while challenges range from analytics culture to data quality. The literature also highlights analytics potential for enhancing efficiency, trust, and service quality.

2.2. Theoretical background

Public procurement, as a critical component of the public sector, requires efficient and strategic use of information systems (IS) and IT to ensure transparency, fairness, and value for money. Adopting these technologies within the procurement domain shapes how governments and public entities purchase goods and services [35]. Several theoretical models have been proposed to illustrate this process and to aid in identifying and managing the complexities of IS/IT adoption. Among these models, the *technology acceptance model* (TAM) [36], the *theory of planned behaviour* (TPB) [37], the *diffusion of innovations* (DOI) [38], and the *technology–organization–environment* (TOE) framework [39] are of particular significance. While TAM and TPB primarily focus on individual-level analysis, the DOI and TOE are especially relevant to public organizations and emphasize organizational-level dynamics [40].

In this study, we chose to incorporate the TOE framework into public procurement, based on a view of public procurement as a dynamic system with numerous interrelated components [41]. In this context, data analytics can be perceived both as a tool and as part of a system: as a tool, it aids procurement officers in making informed decisions based on analyses of data sets related to suppliers, market trends, and historical purchasing data [42]; as part of a system, it acts as a feedback mechanism that can continuously refine the procurement system. Insights collected from data analytics can highlight inefficiencies, detect abnormalities that might suggest fraud, and predict future procurement needs. When looped back into the public procurement system, this feedback leads to iterative improvements, ensuring that the procurement process remains transparent and adaptive to changing circumstances [43]. In systems theory, feedback loops are vital for assessing and adjusting the outcomes of a system to enhance its functionality [44]. In the public procurement system, these loops become necessary to enable public procurement activities to be adjusted to the outcomes. For instance, after analysing a series of tenders, the results from spend analytics might suggest that the environmental footprint of a specific product or service is higher than the market average. When fed back into the system, this insight can lead to revised procurement strategies, or a re-evaluation of the specifications used to ensure sustainability [45]. The TOE framework [39] is a conceptual model used to analyse the factors influencing the adoption of technological innovations in organizations (see Figure 2).

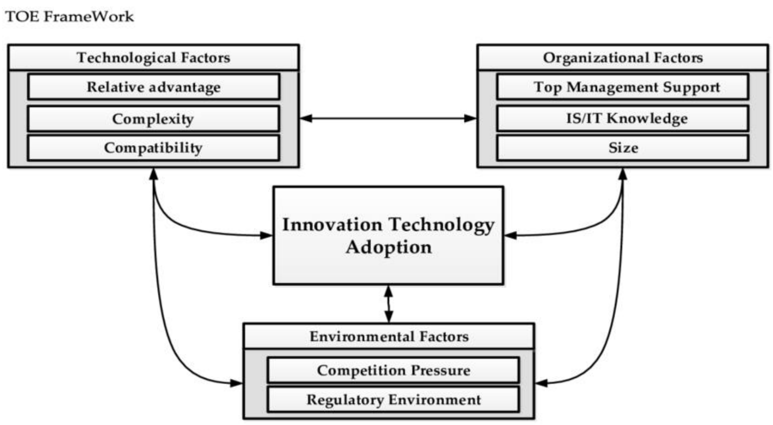

Fig. 2. The TOE framework adopted from Tornazky and Fleischer [39]

It considers three main dimensions: technological (technological readiness and features); organizational (size, structure, and resources); and environmental (industry characteristics, market competition, and regulatory environment). This framework aids researchers and practitioners in understanding and predicting technology adoption behaviours. The adoption of the TOE framework provides a broad lens, enabling researchers to explore how the organizational setting influences the adoption of technological innovations. The TOE framework has been applied in past studies examining the adoption of data analytics in private (e.g. [46]) and public enterprises (e.g. [47]), and its robustness and relevance have been highlighted.

2.2.1. Technological aspects

This theoretical framework emphasizes the role of existing technological infrastructure and the presence of digital resources in assessing an organization's digital transformation readiness. According to Trenerry et al. [48], evaluating an organization's technological readiness should be a variable related to analytics adoption. They argue that the degree to which an organization utilizes digital tools reflects its adaptability to new technology trends.

Within this context, Handfield et al. [32] argue that it is also essential to analyse the influence of analysis expertise, as this significantly contributes to the uptake of spend analytics, thereby underlining the importance of procurement process know-how. The skillset available within the organization shapes its capacity to deploy and maximize the benefits of spend analytics, making it a vital factor affecting adoption. The interaction between the use of digital tools and their potential negative relationship with analytics uptake also merits investigation, and this may suggest that a preference for these tools could hinder the strategic application of analytics [49]. Incorporating a digital procurement approach into the analysis underscores the deliberate adaptation of technology, thereby facilitating the consolidation of expenditure insights [50]. Proficiency in digital tools should also be included in a thorough examination of the adoption of spend analytics [51].

The following hypotheses capture the relationships between technological factors and the adoption of spend analytics:

H1: Using digital tools in the procurement process is positively correlated with adopting spend analytics.

H2: Employees' expertise in analytics is positively correlated with the adoption of spend analytics.

2.2.2. Organizational aspects

When exploring the organizational factors influencing technology adoption, it is crucial to investigate how various characteristics may affect the uptake of spend analytics in public procurement. According to a study by Liberatore et al. [52], organizational size is a crucial consideration, as previous research suggests that larger organizations have more complex operations and thus may be more likely to invest in data analytics. In addition, work by Yao et al. [53] has shown that a central purchasing unit is another variable that warrants attention, as centralized procurement functions are expected to influence the extent and effectiveness of spend analytics adoption based on the argument that centralization can streamline procurement practices and enhance analytical capabilities. A study by Borkovich et al. [54] suggests that organizational roles and the number of procurement employees are also worth inclusion in the analysis. The diversity of the roles within a business provides insight into the differing impacts on technology adoption, as some roles may prioritize spend analytics differently. Finally, Chong and Olesen [55] suggest that the perceptions of management can act as a barrier to technology adoption and are essential to consider. The management's stance towards innovation can significantly influence the organizational culture and readiness for change, making this a potential factor in successfully implementing spend analytics.

These features – organizational size, centralization, role in business, procurement employee numbers, and management's role as a barrier – form a framework for analysing the organizational readiness and potential for spend analytics adoption. This framework is aligned with the many-sided nature of organizational dimensions in the TOE framework, which include culture, leadership, and resource allocation. It is crucial for understanding and predicting technology adoption patterns in public procurement.

To investigate the impact of organization-related factors on spend analytics, the following hypotheses were formulated:

H3: The size of the organization is positively correlated with the extent of spend analytics adoption in public procurement.

H4: The presence of a centralized procurement unit is positively correlated with the extent of spend analytics adoption in public procurement.

2.2.3. Environmental aspects

The environmental dimensions of the TOE framework include the industry structure, regulatory environment, and public funding. The choice to include zero/low-emission solutions in this analysis stems from observations – for example, by Bellucci et al. [56] – that environmental sustainability initiatives often intersect with organizational technology strategies. Researchers can clarify the effect of environmental strategies by conducting spending analytics and focusing on solutions that result in zero or minimal emissions.

Functionality barriers provide a lens for understanding the specific challenges organizations face regarding technology implementation. The perceived value of digital tools is a critical aspect of an organization's environment and influences both the perceived need for and potential resistance to spend analytics. As organizations struggle with functional challenges, they may be more motivated to adopt advanced analytical tools to navigate and mitigate these barriers [57]. Procurement collaboration is another environmental factor that impacts the external business practices influencing an organization's technology adoption. This aspect of the environmental context captures the trends and pressures of inter-organizational cooperation, which can create arenas for exchanging best practices, including the application of spend analytics [58]. Competence barriers represent the external environment, where the general competence level may be a barrier to adopting analytics [59]. Lastly, established routines within organizations can signify both stability and stagnation. Investigating these routines is vital to understanding how a lack of established routines may challenge implementing spend analytics. Analysing these routines within the environmental context can reveal the degree of flexibility and readiness for organizational change, which is crucial for adapting and integrating technology [60]. The regulatory environment can also enable or hinder technology adoption, depending on its alignment with data governance standards.

The following hypotheses were therefore formulated to investigate the environmental dimension:

H5: External policies are significant facilitators for the implementation of spend analytics.

H6: The ease of access to technology within the environmental context significantly facilitates the implementation of spend analytics.

As the existing literature suggests, many factors can affect the adoption of data analytics and DDDM in public organizations. Figure 3 provides an overview of the factors identified in the literature.

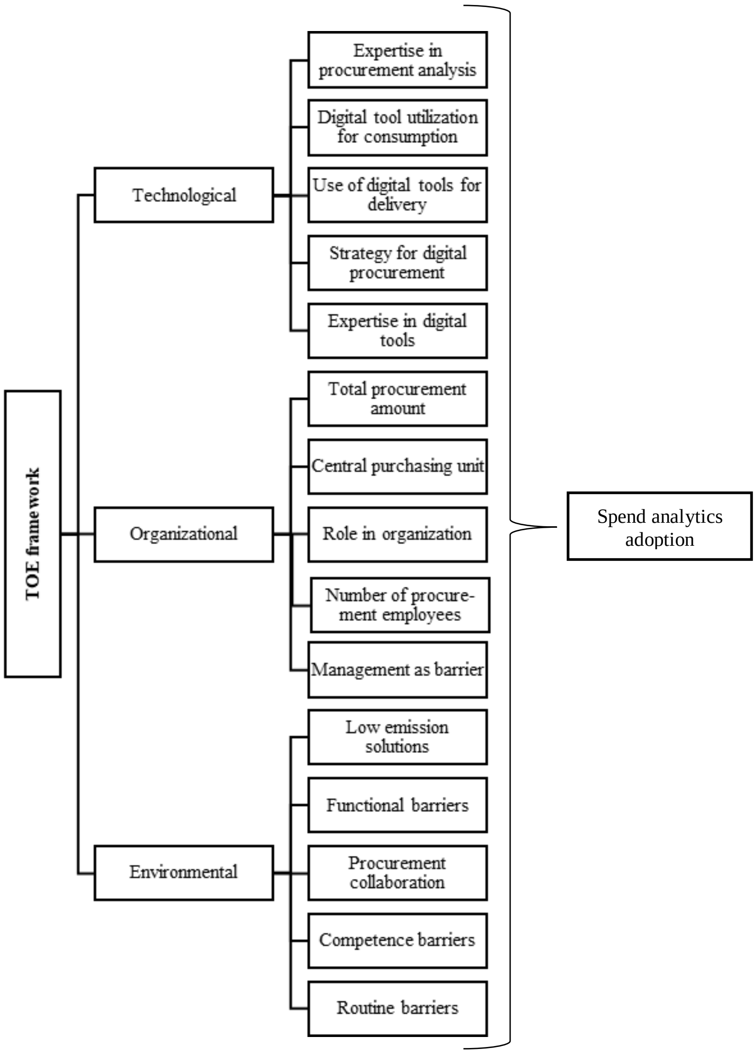

Fig. 3. TOE factors affecting the adoption of data science and analytics in public organizations.

3. Research method

In this section, we outline the methodological approach adopted in this research to explore the elements influencing the adoption of spend analytics in public procurement. This methodology underpins the research design, data collection, and data processing and analysis procedures.

3.1. Research design

We adopted a quantitative cross-sectional survey design based on secondary government data from 2022 in Norway. The design captured a specific moment in time [61] to provide insights into the current practices, perceptions, and barriers associated with adopting spending analytics within public procurement entities in Norway. The study was structured to allow us to statistically evaluate the relationships between various factors categorized within the TOE framework and their impact on adopting spend analytics. The survey included a wide-ranging set of 276 variables. Based on our literature review, this study looked more closely at 15 factors (see Figure 3) reflecting aspects critical to adopting procurement analytics. This structured approach allowed us to measure the extent to which public procurement entities have adopted spend analytics into their operations. We also explored the strength and nature of the associations between adopting spend analytics and the potential determinants identified in the TOE framework. Although it offers valuable insights into the factors influencing the adoption of spend analytics, this study's nature imposes limitations on establishing causality. Nevertheless, the correlations investigated here provide a foundation for understanding the current adoption landscape and can serve as a springboard for further studies, which could track changes over time and potentially reveal causal relationships [62].

3.2. Data collection

The survey was conducted by the Norwegian Agency for Public and Financial Management. The Agency conducts a biannual survey as part of a broad effort to understand the current state of public procurement in Norway. The survey's target was procurement managers from a wide array of public entities, including state enterprises, counties, and municipalities, and the survey focused on entities and respondents directly involved in public procurement to ensure the quality and relevance of the collected data. In 2022, the survey was distributed electronically, which allowed for a higher response rate and adherence to data integrity principles. This strategy led to 578 responses from 1132 public companies in Norway, representing a response rate of approximately 51%, thus offering a rich and diverse data set for analysis. The responses were spread across public organizations, as seen in Table 2.

Table 2. Overview of responses from different types of government procurement entity

Type of public entity	**Percentage of respondents**
Municipality	42%
Public enterprise and company	29%
State enterprise	28%
County	1%

The survey aimed to provide a broad overview of public procurement, focusing on governance, operation of the public procurement process, competence, time and resources, sustainability, innovation, and digitalization. Our target variable was the question, 'What surveys and analyses are carried out concerning planning your total purchasing portfolio?'. Spend analysis was one of the alternatives (sl_an_spend). This structured approach to data collection, the wide range of variables, and the survey question explicitly asking about spend analytics were crucial to gaining insights into adopting spend analytics in public procurement in Norway. The resulting data set was therefore positioned to support a many-sided analysis, offering valuable perspectives on the technological, organizational, and environmental influences on the adoption of spend analytics.

3.3. Data preparation and analysis

To ensure the integrity and robustness of the findings of this study, data preparation and analysis were conducted with careful attention to detail, following established protocols in the field [63]. The Norwegian Agency for Public and Financial Management provided the data set, which consisted of survey responses from various public procurement entities in Norway. However, we found several critical issues with the data set regarding survey design and data management. Firstly, missing values from the data set can skew the results and limit the data's representativeness. Mixing integers and decimals in coding also introduces inconsistencies in data types, complicating data processing and analysis. Using unusually large values (e.g. 400) can be problematic, as they may represent outliers or data entry errors that can distort statistical findings.

Moreover, the inclusion of zero as a value, depending on the context, may represent either a legitimate data point or a placeholder for missing or unrecorded data, which adds to the ambiguity. The data set also exhibited unclear and inconsistent coding practices, as evidenced by a feature containing an inconsistent array of values such as 0, 1, 12, 400, 1.5, 40, and 150. This wide range suggests a lack of standardized data entry protocols or a misunderstanding of the nature of the data, making it challenging to interpret or analyse these values meaningfully. Finally, the use of long attribute names poses technical challenges, as some data analysis libraries or software may have limitations on character length, leading to errors during data processing. This issue, while seemingly minor, can cause significant practical difficulties in data handling and analysis. Overall, these problems collectively undermined the reliability and validity of the data set, meaning that thorough cleaning and standardization were needed before any meaningful analysis could be conducted.

Hence, systematic data cleansing and preparation processes were employed to mitigate the risk of bias arising from incomplete or inconsistent data. Although the data set had several design issues, it contained a rich array of continuous and categorical variables. Out of a comprehensive collection of 276 variables, 15 were chosen based on the literature and the alignment with the TOE framework, which guided the analysis of factors influencing the adoption of spend analytics. These variables covered a spectrum, from technological tools and digital maturity to organizational characteristics and the wider business environment. The data set also contained attributes with missing values and outliers, which required imputation strategies tailored to their data types. For example, median values were substituted for missing entries in numeric columns as they are less sensitive to outliers [64]. In addition, to ensure consistency in textual columns, all textual values were converted to lowercase. Categorical variables, such as the type of public entity and the number of employees, were also converted to a binary matrix; this was necessary for the subsequent regression analysis, as it enabled us to use numerical techniques to process and analyse categorical data effectively [65]. As the features in the data set had different ranges, the preparation process also included min-max normalization. This technique maintains the shape of the original distribution while scaling the values to a specific range, typically zero to one. This technique can be instrumental in ensuring that no single feature disproportionately dominates the others [66]. Following data preparation, descriptive statistics were generated to provide an initial overview of the characteristics of the data. This foundational step involved calculating the frequency distributions, percentages, means, and standard deviations of the variables under consideration. This allowed us to identify general patterns, trends, and potential anomalies within the data set to prepare for more complex analyses [65]. The study then progressed to a correlation analysis, which explored the relationships between the selection of factors captured in the survey and the target variable ′sl_an_spend�much, denoting the adoption of spend analytics in procurement planning [67]. The correlation coefficients provided a measure of the strength and direction of the linear relationships between the variables. This analysis was central in identifying which factors showed the most substantial associations with the adoption of spend analytics, thus identifying potential areas of interest for deeper investigation. Hypothesis testing was conducted using chi-square tests of independence to validate the findings of the correlation analysis. These tests involved determining the significance of the relationships between variables and the adoption of spend analytics [68]. After determining the statistical significance of the observed associations, the study moved beyond exploratory data analysis to a confirmatory data analysis, thus providing a better understanding of the factors influencing the adoption of spend analytics.

A commitment to methodological quality supported this multifaceted approach to data analysis. Each step was executed carefully, from the *Norwegian Agency for Public and Financial Management's* initial survey design to the data analysis process. This ensured that the conclusions drawn about the status and determinants of adopting spend analytics in Norwegian public procurement were based on empirical evidence and stood up to a thorough statistical study. Finally, even though the data set suffered from significant issues, by following best practices in data handling and statistical analysis, the study provided a reliable and insightful examination of the factors contributing to adopting spend analytics in public procurement in Norway.

4. Findings

In this section, we explore the data gathered from the survey to reveal the dynamics of the adoption of spend analytics within public procurement in Norway. We first present some descriptive findings, then examine in more depth the correlation analysis and hypothesis testing results.

4.1. Descriptive findings

In this section, we explore the descriptive statistics that summarize the findings on spending analytics in public procurement. Our data set consisted of 578 responses, of which there were 529 valid responses on adopting spend analytics. The standard deviation, a key measure of dispersion, was 0.458; this indicates a moderate spread in the data. It suggests that while there may be some consensus on specific aspects of spend analytics, there is also significant diversity in how the respondents utilize and perceive it. This variance highlights the need to examine the factors affecting the adoption of spend analytics in procurement processes. Table 3 shows the distribution of respondents' roles who answered the 'sl_an_spend' question in percentages.

Table 3. Roles of respondents

Role	**Percentage of respondents**
Procurement manager with personnel responsibility	29%
Procurement coordinator without personnel responsibility	29%
Economic or administrative manager	19%
Purchaser	7%
Technical specialist	5%
Budget owner	3%
Project manager	1%
Other roles	7%

The breakdown shows the roles of the individual respondents who provided insights into adopting analytics within their organizations. Of these, approximately 39% of the respondents reported using spend analytics, while 61% did not use spend analytics in their procurement planning (see Figure 4).

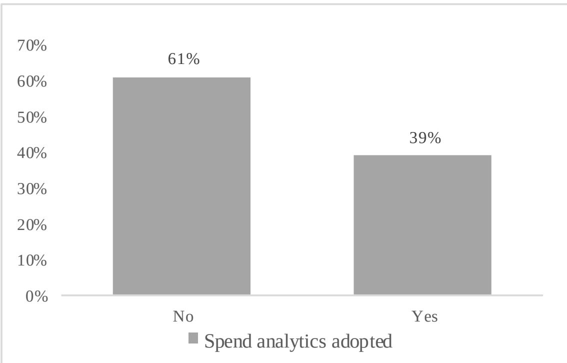

Fig. 4. Adoption of spend analytics in procurement planning.

Table 4 shows the percentages of public entities in Norway within each category that do not use spend analytics. In state enterprises and public enterprise companies, the majority (66% and 65%) do not use analytics in their procurement planning. In municipalities, 56% do not conduct spend analytics. County municipalities report a higher adoption rate, with only 38% not using spend analytics.

Table 4. Overview of entity type and percentage that do not conduct spend analytics.

Type of public entity	Do not conduct spend analytics
State enterprise	66 %
Public enterprise companies	65 %
Municipality	56 %
County	38 %

These descriptive findings give a foundational understanding of the analytics landscape in Norwegian public procurement. A correlation analysis of the identified factors based on the TOE framework was conducted to understand which factors influence the use of analytics in procurement planning. The findings of this analysis are presented in the following section.

4.2. Correlation analysis

As discussed earlier, the technological, organizational, and environmental contexts identified in the literature could potentially affect public organizations' adoption and use of data analytics. Our findings are, therefore, organized and presented according to the three main dimensions of the TOE framework.

4.2.1. Technological context

The technological background is vital in understanding the landscape of analytics adoption within public procurement and relates to both the internal and external technologies relevant to the organization. It involves the technologies available to the firm as well as the technologies currently in use. The heatmap in Figure 5 offers insights into the correlation between the various technological dimensions and the adoption of analytics.

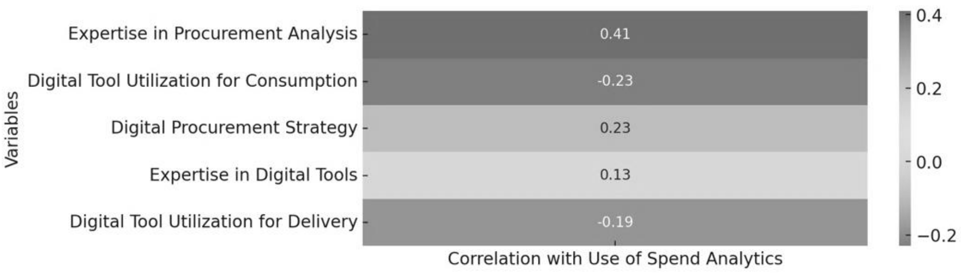

Fig. 5. Correlations top five technological context variables.

We find that expertise in procurement analysis positively correlates with adopting spend analytics, with a correlation of 0.41, highlighting the importance of analytics competence in adopting analytical tools. In contrast, a correlation of −0.23 for digital tool utilization for consumption indicates an inverse relationship. The presence of a digital procurement strategy is correlated with a value of 0.23, representing a modest positive effect on the likelihood of adopting spend analytics. With a correlation of 0.13, expertise in digital tools has a slight positive impact on adopting spend analytics. Lastly, a correlation of −0.19 for digital tool utilization for delivery suggests that prioritizing digital delivery tools has a low negative correlation with adopting spend analytics. These correlations illustrate the roles played by expertise in procurement analytics in the adoption of spend analytics while also revealing the nuanced interplay with the practical use of digital tools.

4.2.2. Organizational context

The organization's context, such as its size and internal structure, has drawn significant attention in the literature. We conducted a correlation analysis to clarify the organizational factors influencing this adoption. The findings are shown in the correlation heatmap in Figure 6.

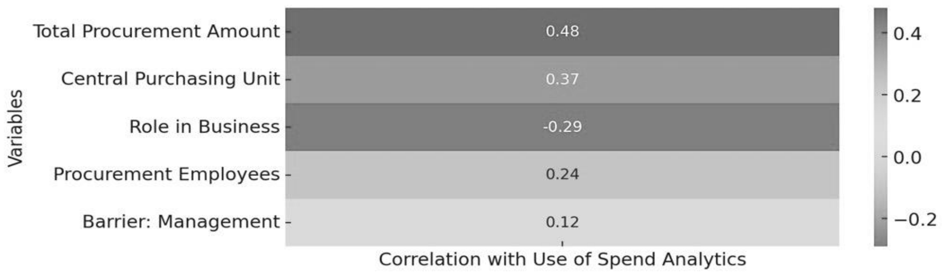

Fig. 6. Correlations of the top five variables related to the organizational context

The heatmap for the organizational context describes the relationship between organizational characteristics and the adoption of spend analytics in public procurement. The findings reveal that organizations with higher total procurement volumes show a positive correlation of 0.48 with adopting spend analytics. The presence of a central purchasing unit correlates with 0.37, indicating that organizations with structures of this type are more likely to implement spend analytics. The negative correlation of −0.29 associated with the role in business suggests that specific organizational roles and priorities may negatively affect the adoption of spend analytics. The number of procurement employees has a moderate positive correlation of 0.24 with the adoption of spend analytics. The perception of management as a barrier shows a small positive correlation of 0.12. These correlations reveal the influence of the organizational structure and perceived barriers on the integration of spend analytics, with the size of the procurement amount and centralization being facilitative factors. Simultaneously, the particular position one holds in the business and the prevailing management attitudes subtly impact the trend of adoption.

4.2.3. Environmental context

To explore the environmental context, we focused on the external business environment variables identified in the extant literature and within the TOE framework's context. The heatmap in Figure 7 shows the influence of environmental factors on adopting spend analytics in public procurement.

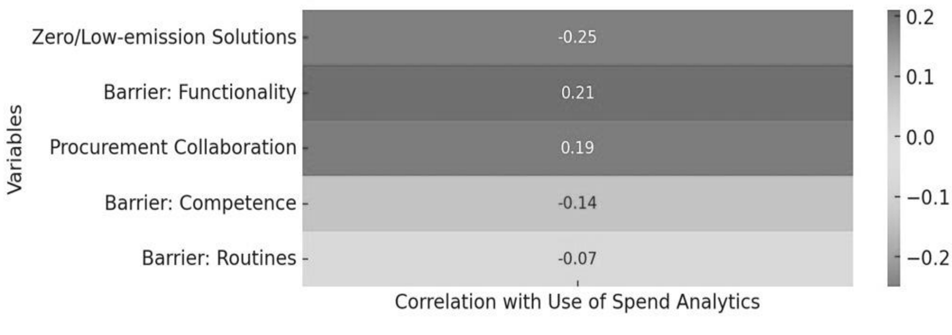

Fig. 7. Correlations of the top five variables in the environmental context

The findings show a moderate negative correlation of −0.25 with zero/low-emission solutions, a positive correlation of 0.21 with functionality barriers, a small positive correlation of 0.19 with procurement collaboration, and a small negative correlation of −0.14 for competence barriers. Finally, the weak negative correlation of −0.07 for established routines indicates that established practices in organizations have a slight negative impact on adopting spend analytics. Although the correlations showed some trends, all of them were weak, and it was difficult to conclude the relationship between the environmental context and adoption. Based on the findings of the correlation test, we carried out further tests of the hypotheses constructed from the literature review.

4.3. Hypothesis testing

The exploration of hypotheses in this study involved empirical tests of the theoretical statements concerning the adoption of spend analytics in Norway's public procurement. Conducting hypothesis testing allowed us to move from preliminary observations to a more data-driven understanding of the factors influencing this adoption. The statistical validation process involved presenting the outcomes of regression analyses, supported by numerical evidence, to establish the validity of the proposed relationships (see Table 5).

Table 5. Results of hypothesis testing

Hypothesis	**Variable**	**Coefficient**	**P-value**	**Support**
H1: Using digital tools in the procurement process is positively correlated with the adoption of spend analytics.	Use of digital tools	−0.23	0.045	Not supported
H2: Employees' expertise in analytics is positively correlated with the adoption of spend analytics.	Analytics expertise among employees	0.41	< 0.001	Supported
H3: The size of the organization is positively correlated with the extent of spend analytics adoption in public procurement.	Organizational size	0.48	< 0.001	Supported
H4: The presence of a centralized procurement unit is positively correlated with the extent of spend analytics adoption in public procurement.	Centralized procurement unit	0.37	< 0.001	Supported
H5: External policies are significant facilitators for the implementation of spend analytics.	Zero- and low-emission solutions	−0.25	0.034	Not supported
H6: The ease of access to technology within the environmental context significantly facilitates the imp**lementation of spend analytics.**	Functionality not being perceived as a barrier	0.21	0.060	Not supported

Hypotheses H1 and H2 are centred on the premise that the proficiency of employees in analytics and the use of digital tools are significant determinants of the adoption of spend analytics. The regression output provides a divided picture: whereas employee expertise in analytics emerges as a positive influence on adoption (as evidenced by a coefficient of 0.41 and p-value below 0.001), the use of digital tools paradoxically shows a negative association, although this is not significant, with a coefficient of −0.23 and a p-value of 0.045. The data lend robust support for hypotheses H3 and H4, which relate the size of the organization and the presence of a centralized procurement unit to the adoption of spend analytics. A larger procurement amount positively correlates with adoption, as indicated by a coefficient of 0.48 and a significance level below 0.001. H4, which relates to the centralization of procurement functions, is also supported, with a positive coefficient of 0.37 and a high significance level. Hypotheses H5 and H6 relate to the broader environmental context, including external policies and technology accessibility, as a promoter for adoption. The regression analysis shows that zero/low-emission solutions show a moderate negative correlation of −0.25 with a p-value of 0.034, and the non-perception of functionality as a barrier has a positive coefficient of 0.21 with a p-value of 0.060. Both fall short of the established significance thresholds, meaning that statistical evidence to support H5 and H6 is not provided. This outcome suggests that while favourable environmental conditions promote adoption, zero/low-emission solutions and functionality as a barrier do not have a statistically significant effect. The results of this study illustrate that the adoption of spend analytics in public procurement is influenced by a collection of factors, including competence in analytics and procurement amount. The presence of a centralized procurement unit is shown to have a positive effect based on statistical verification. The findings partially support H1, H2, H3, and H4, but do not support H5 and H6. This underscores the many-sided nature of DDDM adoption in public procurement, which will be discussed further in the next section.

5. Discussion, research implications, and limitations

In this section, we explore the many-sided adoption of spend analytics in Norwegian public procurement and interpret the study's findings, drawing on the TOE framework to explain the current state and influence of various factors on adopting spend analytics. We evaluate the paradoxes and correlations revealed in the findings and examine the outcomes of hypothesis testing. This section will also discuss the implications of these findings for policymakers in promoting a systemic adoption approach and the need for further research into the influencing factors. The limitations of this study are identified, and we highlight the challenges posed by the data set and self-reporting biases.

5.1. Research question and main findings

This study investigated the following research question: What is the status of spend analytics adoption in public procurement in Norway, and what are the technological, organizational, and environmental factors influencing this adoption?

Adopting spend analytics within Norway's public procurement system presents an interplay of technological, organizational, and environmental factors, as evidenced by the data drawn from 529 public procurement entities. Despite the potential benefits of spend analytics, the overall adoption rate is a modest 39%, indicating significant room for growth and integration within various government organizations.

With regard to technological factors, our research finds a significant positive correlation between employees' analytical expertise and the adoption of spend analytics (H2). This suggests that the human factor, specifically the skill level in analytics, is critical in leveraging technology to drive efficiency within procurement processes. The investment in developing such expertise is validated as a determinant of successful adoption. Conversely, the study reveals an unexpected negative correlation between using digital tools and adopting spend analytics (H1). This result is counterintuitive, as digital tools are typically seen as enablers of analytical processes. The negative relationship could imply that the presence of digital tools alone is insufficient or that their current utilization is not optimally aligned with strategic analytical objectives. It encourages a reassessment of how digital technologies are employed and suggests the need for a strategic framework that better integrates these tools with analytics functions.

Organizational factors also play a vital role in the adoption of spend analytics. The data shows that larger organizational sizes (H3) and the presence of centralized procurement units (H4) are positively associated with higher adoption rates. These findings support the notion that scale, and structured procurement environments can create an encouraging atmosphere for adopting analytics. Larger entities may possess the requisite resources and centralized control necessary for implementing complex analytical systems, unlike smaller entities facing resource constraints.

When examining environmental factors, our study introduces a layer of complexity regarding adopting spend analytics. A counterintuitive negative correlation exists between the emphasis on zero- and low-emission solutions and the use of spend analytics (H5). At first glance, one might assume that spend analytics would support sustainability goals by identifying opportunities for emission reductions and eco-friendly procurement decisions. However, the negative correlation could indicate a discrepancy between the intentions of environmental policies and the practical integration of analytics into achieving these goals. Why this is so requires further research.

Moreover, while generally perceived positively, access to technology within the procurement environment does not show a strong predictive relationship with the adoption of spend analytics (H6). Although accessibility is favourable, it may not be a significant driver of analytics adoption, suggesting that other barriers, possibly related to the functionality and integration of technology, may exist. The factors found to have the highest positive significant correlations with the adoption of spend analytics in our data are presented in Figure 8 below.

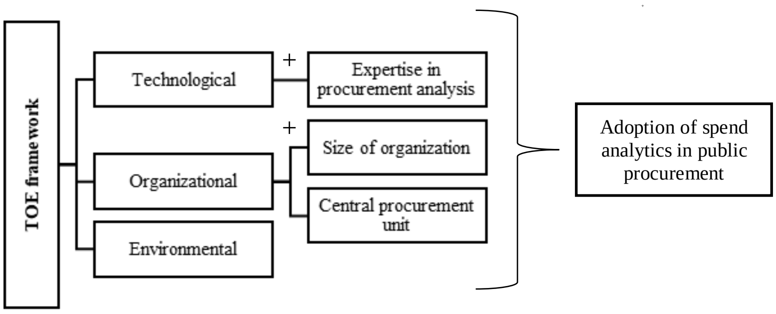

Fig. 8. Factors positively related to the adoption of spend analytics in public procurement in Norway

5.2. Spend analytics in Norwegian public procurement: Adoption and impact.

The findings of our study regarding the adoption of spend analytics in Norwegian public procurement reveal the system's complexity, where technology is not merely an infrastructural element but also a tool and feedback mechanism, as articulated in Thai [41] and Tan and Lee [42]. Consistent with systems theory [44], the adoption and impact of spend analytics are better understood as part of a dynamic system where data analytics enhances decision-making and simultaneously serves as a feedback loop, which refines procurement processes over time [43].

Our research differs from our earlier study by employing a newer survey data set and focusing on another target variable [26]. The previous study did not find any significant relationships, but the findings of this study show that analytics skills, centralization of procurement, and size have significant effects. These results reflect the complex connections between strategy, competence, digital tool usage, and analytics adoption, and the unexpected negative impact of digital tool expertise on adoption rates, suggesting a misalignment that may stem from the systemic disconnect between operational and strategic IT use. In a feedback-oriented public procurement system where insights from analytics can iteratively improve procurement strategies, this insight supports the notion that adopting analytics forms part of a more extensive feedback system where operational practices must be aligned with strategic goals to optimize the use of technology within the procurement system. Ghosh [27] emphasized the role of IT infrastructure and internal capabilities. Our findings partially support this view, as procurement volumes and analytics competence correlate positively with analytics adoption. However, our study did not find the expected positive impact of digital tool usage. Our findings on the negative impact of digital tool expertise conflict with those of a study by Weng [29], in which business strategies were linked to adopting analytics. This could imply that while strategy informs intention, operational tool use may not necessarily support the strategic deployment of analytics, suggesting a potential misalignment between operational and strategic IT use in public procurement. Although our study recognizes the critical role of technological advancements and standardized data protocols, as discussed by Merhi and Bregu [28] and Handfield et al. [32], the lack of direct influence of advanced technology on the adoption of analytics may suggest systemic barriers such as data quality issues. In addition, the challenge of adopting spend analytics is tied to the evolving nature of procurement roles, as highlighted by Farshchian et al. [30], which points to systemic challenges within organizational change management and the need for clarity in defining new roles in the context of DDDM tools. This finding underscores the importance of feedback in role evolution and adapting processes within the procurement system. Finally, our findings support those of LaValle et al. [34], van Ooijen et al. [12], and Westerski et al. [33] that DDDM can enhance public trust and service quality, meaning that a structured approach to spend analytics is indicative of a mature public procurement system. This structured approach recognizes the procurement function as part of an overarching system where spend analytics can lead to more informed decision-making and improved public trust. The contrast between the low adoption rate of procurement analytics and the potential benefits of DDDM, as highlighted by Moretto et al. [25] and Patrucco et al. [10], aligns with our study's findings of the underutilization of spend analytics in Norway, despite the levels of technological advancement and digitalization in the country.

In general, this research contributes to the dialogue initiated by previous studies by underscoring the multisided nature of adopting analytics in public procurement. It reveals several contradictions and complements existing theories by suggesting that the relationship between technology use and analytics adoption is not linear and may be mediated by factors such as size, organizational structure, and perhaps even competing priorities such as sustainability goals. The insights from our study highlight the need to recognize public procurement as a complex system in which spending analytics is a critical component. This system-oriented perspective suggests that future efforts to increase the adoption of spend analytics must consider the systemic interdependencies that shape public procurement.

5.3. Implications

Although integrating spend analytics within Norway's public procurement systems represents a complex endeavour, our findings suggest some starting points for adoption. We address the central question of how spend analytics is adopted, and this research, based on the determinants of the TOE framework, enriches the academic debate, and informs public entities regarding improving the public procurement system. Our analysis shows how incorporating spend analytics into public procurement in Norway can enhance decision-making and reflect the combined influence of analytical competencies, organizational traits, and external factors. For policymakers, the findings underscore the need to develop an analytics-centric organizational culture rather than concentrating solely on technological provision. In addition, investment strategies should extend beyond acquiring tools to their incorporation into strategic processes to optimize the effectiveness of public expenditure, as set out in the World Bank's guidelines [3]. Moreover, personnel training to enhance analytics capabilities is critical to fully exploit technological investments and realize the potential of DDDM [16].

From an academic perspective, our results call for extended research into the complex factors shaping the adoption of spending analytics. Investigating the interplay with organizational behaviour and regulatory backgrounds would generate more comprehensive insights into the forces shaping the adoption of analytics in the Norwegian public procurement system.

By addressing the primary question of the adoption of spend analytics and its determinants, this research contributes to scholarly discussion. It provides public sector agencies with guidelines for the adoption of analytics. These insights may facilitate informed decision-making and policy development in future public procurement.

5.4. Limitations

Our attempt to investigate the adoption of spending analytics status quo among government entities in Norway offers a snapshot of the current practices but is subject to certain limitations. In particular, the complexity and untidiness of the data set pose challenges, as it includes instances of non-responses that may affect the robustness of the findings. In addition, the data set suffers from multiple issues that affect its suitability for this analysis, including mixed data types (integers and decimals), large and potentially erroneous values, and ambiguous uses of zero values. Inconsistent coding and long feature names also create challenges regarding data interpretation and technical processing. To address these issues in future data collection and survey design processes, we recommend implementing standardized data entry protocols to ensure consistency in coding and data types. Handling missing values with imputation techniques or exclusion, depending on the context, can also improve data quality. However, the issue of missing data is shared with surveys and frequently poses challenges for researchers analysing surveys and various questionnaires, as respondents often leave some items unanswered [69]. This lack of responses complicates the execution of statistical analyses and the computation of research scores [69]. In addition, simplifying the feature names and ensuring compatibility with analysis software would aid in efficient data processing. These steps are crucial for enhancing the reliability and validity of the data set for future statistical analysis and reducing the time and effort needed during the data cleaning and preparation phases. A reliance on self-reported data could also introduce biases; the respondents' perceptions may not accurately reflect their organizations' realities, as they may be influenced by social desirability or other subjective factors. These elements, although crucial to the adoption of spend analytics, were beyond the scope of our work and were not examined in this study.

The TOE framework adopted in this study may also impose limitations on the research. This framework has been criticized for being too generic and failing to fully account for the interplay between technology, organizational dynamics, and the broader environmental context. For instance, the TOE framework may oversimplify the many-sided nature of organizational change, which involves more than just aligning technological capabilities, organizational readiness, and external pressures. It may also neglect the influence of inter-organizational networks, industry standards, and the role of policy changes over time. Consequently, although the TOE model provides a structured approach to studying technology adoption, it may not capture the details and the full range of factors influencing the implementation and utilization of spend analytics in public procurement.

6. Conclusions and further research

In the current digital era, the potential of data to transform public procurement operations into a strategic function within government remains a central theme. This study has addressed the adoption of spend analytics within Norwegian public procurement and has examined the interplay between the technological, organizational, and environmental factors affecting its adoption. Only 39% of Norwegian public procurement entities have adopted spend analytics, and our findings show that this sector is on the edge of transformation and is still navigating the shift toward comprehensive data-driven practices. Organizations are at the beginning of the process of embracing data analytics to enhance public procurement. This study illuminates the multifaceted nature of adopting spend analytics in public procurement in Norway and emphasizes the importance of technological competence, organizational scale, and strategic alignment. The significant positive impacts of analytics expertise and organizational structure on adoption highlight the need for a strategic, analytics-centric culture.

In contrast, the surprising negative correlation between digital tool usage and analytics adoption indicates a potential strategic–operational misalignment. The findings suggest that public procurement should be recognized as a complex, feedback-oriented system in which operational practices are aligned with strategic goals. For policymakers, these insights mean that a systemic approach to adoption is needed, integrating analytics into strategic processes and emphasizing the development of analytics capabilities.

Future research should explore the complexities of spend analytics adoption through a mixed-methods approach, and qualitative and quantitative analyses should be employed to address the shortcomings of the current research. Qualitative methods, such as in-depth interviews or focus groups, could provide richer, contextual insights into the motivations, barriers, and cultural nuances that support the adoption of analytics in public procurement. Sector and country-specific investigations could further refine the understanding of these dynamics and allow for more tailored and effective recommendations. In addition, better-structured data sets, which could be obtained through established and controlled data collection and management methods, would help clarify the long-term patterns in adopting spending analytics within this vital function of government.

Finally, Norway stands at a crossroads regarding realizing the full potential of data analytics in public procurement. This study provides insights allowing stakeholders to strategize effectively toward an analytic-centric procurement system. It underscores the many-sided nature of adoption and signals that the journey towards spending analytics-empowered public procurement is ongoing, with opportunities for public procurement to develop as a strategic part of government.

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