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The mission of the IJISPM - International Journal of Information Systems and Project Management - is the dissemination of new scientific knowledge on information systems management and project management, encouraging further progress in theory and practice.

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- management of complex projects
- audits
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- ethics
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- project environment
- project management life-cycle
- project initiation
- project planning
- project execution
- project control and monitoring
- project closing
- success criteria and success factors
- project manager role
- project manager skills
- portfolio management
- program management
- managing organization - structure
- tools and techniques
- project evaluation
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- project management knowledge areas
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Editorial

The mission of the *IJISPM - International Journal of Information Systems and Project Management* is to disseminate new scientific knowledge on information systems management and project management, encouraging further progress in theory and practice.

We are pleased to bring you the second number of the 12th volume of IJISPM. In this issue, readers will find important contributions on information systems management, software quality, adoption of information technology, and project management education.

The first article, "Spend analytics in Norwegian public procurement: adoption status and influencing factors", is authored by Marius Langseth and Moutaz Haddara. How decisions are made in public procurement influences nations' economic health and citizens' daily lives. In this study, the authors 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, they found 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.

The title of the second article is "Digital learning, big data analytics and mechanisms for stabilizing and improving supply chain performance", which is authored by Aziz Barhmi Mohammed, Soulaimane Laghzaoui, Fahd Slamti and Mohamed Reda Rouijel. This study attempts to shed light on the nature of the contribution of digital learning orientation (DLO), as an intangible resource, to the development of the dynamic capability of supply chain data analytics powered by artificial intelligence (SCDA-AI) as well as to the moderation of its effects on the enhancement of the operational capabilities of supply chain flexibility (SCFL), supply chain resilience (SCRE) and supply chain responsiveness (SCRES) in order to stabilize and improve supply chain performance (SCPER) in times of uncertainties and disruptions. The study was based on survey data collected from 200 foreign companies based in Morocco. Respondents were mainly senior and middle managers with experience in general management and supply chain (SC). Validity and reliability analyses and hypothesis testing were carried out using structural equation modelling (SEM) with SPSS Amos. The results revealed that DLO acts as an antecedent to SCDA-AI without moderating its effects on the three operational capabilities of SCFL, SCRE and SCRES. In addition, this study provides further empirical evidence that dynamic capabilities can produce significant results in terms of stabilizing and improving performance through the generation and/or reconfiguration of operational capabilities in situations of uncertainties and disruptions.

The third article, authored by Sławomir Wawak, is entitled "Enhancing project quality through effective team management". This study aims to explore the relationship between team management and project quality, identify key contributing factors, and examine the role of employee involvement, commitment, and innovation. An empirical, cross-sectional study was conducted using an online survey to gather data from 510 respondents across various industries, projects, and experiences. Data analysis employed statistical techniques to reveal patterns and trends. Key factors contributing to project success include communication, comprehensive planning, clear roles and responsibilities, stakeholder requirements, and a supportive work environment. The significance of proper management approaches, techniques, and attitudes was also highlighted. The findings contribute to the current body of knowledge on project quality management and emphasize the need for a human-centered management approach to achieve high-quality

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project outcomes. This study sheds light on the pivotal role of effective team management in project quality, providing valuable insights and recommendations for project managers, team leaders, and organizations seeking to improve project performance.

"A comparison of soft factors in the implementation and adoption of digitalization projects: a systematic literature review" is the fourth article and is authored by Bertha Joseph Ngereja, Bassam Hussein and Carsten Wolff. This study expounds existing literature on digitalization projects taking a one-dimensional view on people at organizational, project and individual levels. Through a systematic literature review, the authors highlight and contrast the impact of soft factors on the implementation and adoption of digitalization projects. Four core enablers were identified and contrasted at different organizational levels in an integrated framework for successful implementation and adoption of digitalization projects. Findings indicate that both adoption and implementation of digitalization projects have similar core enablers at organizational level, significantly different actions that need to be taken at project level and slightly different characteristics at individual level. Moreover, eight critical soft factors were identified for successful implementation and adoption of digitalization projects. The findings provide valuable insights to practitioners and enable controlling the highest value factors to increase the success rate of digitalization projects and to identify the core elements that need attention at various organizational levels.

We would like to take this opportunity to express our gratitude to the distinguished members of the Editorial Board for their commitment and for sharing their knowledge and experience in supporting the IJISPM.

Finally, we would like to express our gratitude to all the authors who submitted their work for their insightful visions and valuable contributions.

We hope that you, the readers, find the International Journal of Information Systems and Project Management an interesting and valuable source of information for your continued work.

The Editor-in-Chief,

João Varajão

University of Minho

Portugal

João Varajão is a professor of information systems (IS) and project management (PM) at the University of Minho. He is also a researcher at the ALGORITMI/LASI research center. Born and raised in Portugal, he attended the University of Minho, earning his Graduate (1995), Masters (1997), and Doctorate (2003) degrees in Technologies and Information Systems. In 2012, he received his Habilitation from the University of Trás-os-Montes e Alto Douro. His main research interests are IS PM, IS Development, and IS Management (addressing PM success and the success of projects). Before joining academia, he worked as an Information Technology (IT)/IS consultant, project manager, IS analyst, and software developer, for private companies and public institutions. He has supervised over 140 MSc and PhD theses. He has published more than 300 works, including refereed publications in journals, authored books, edited books, book chapters, and communications at international conferences. He serves as editor-in-chief, associate editor, and editorial board member for international journals. He has served on numerous committees for international conferences. ORCID: 0000-0002-4303-3908

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

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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.

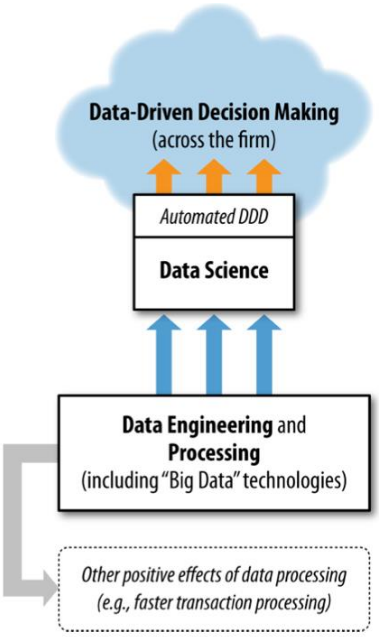

Fig. 1. The DDDM ecosystem adopted from Provost and Fawcett [16]

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).

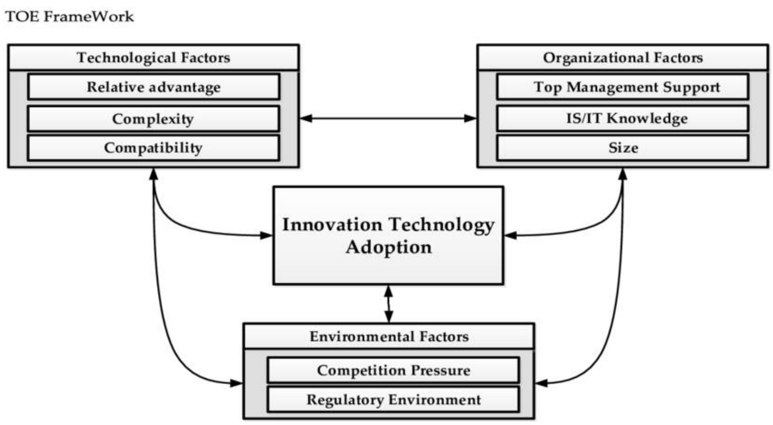

Fig. 2. The TOE framework adopted from Tornazky and Fleischer [39]

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.

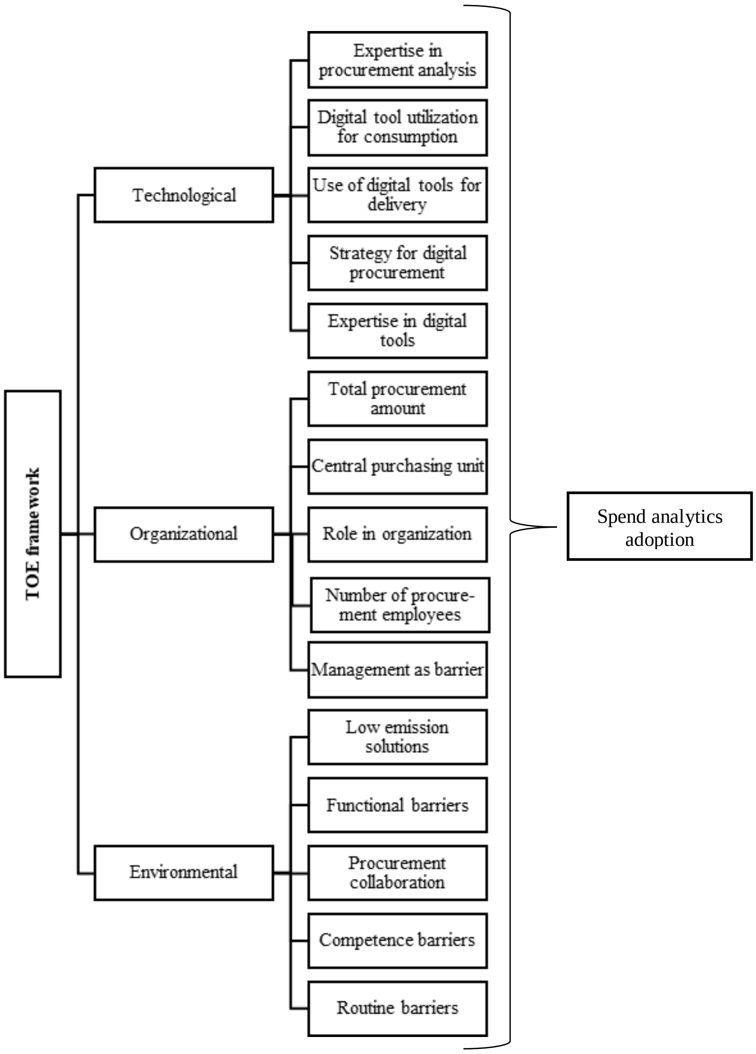

Fig. 3. TOE factors affecting the adoption of data science and analytics in public organizations.

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‵, 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).

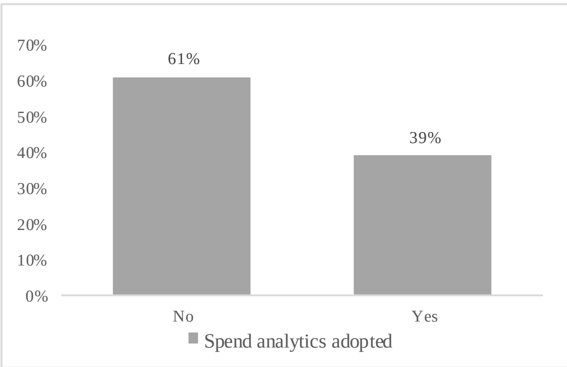

Fig. 4. Adoption of spend analytics in procurement planning.

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.

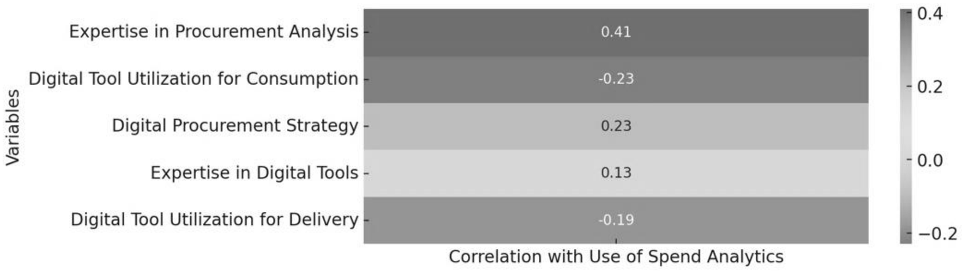

Fig. 5. Correlations top five technological context variables.

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.

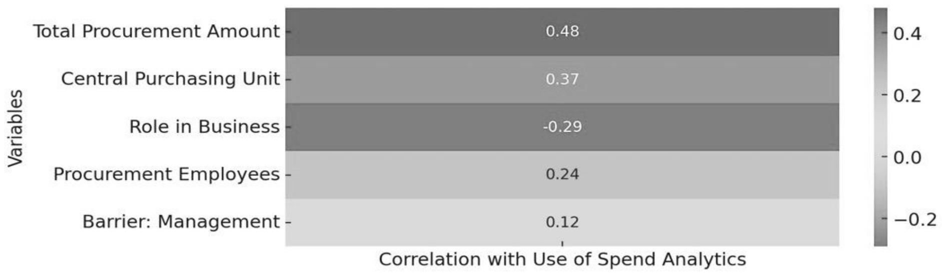

Fig. 6. Correlations of the top five variables related to the organizational context

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.

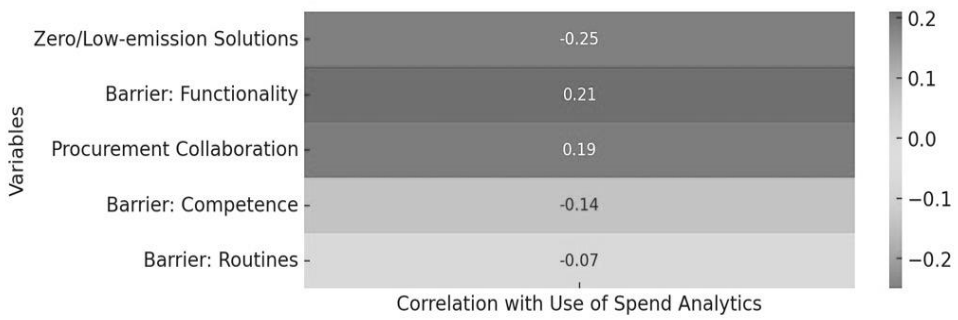

Fig. 7. Correlations of the top five variables in the environmental context

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.

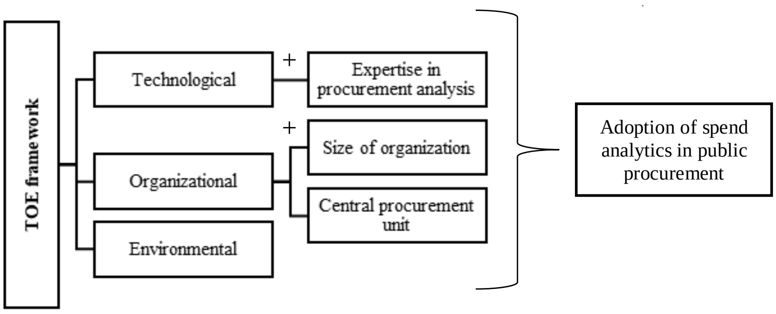

Fig. 8. Factors positively related to the adoption of spend analytics in public procurement in Norway

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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Abstract:
This study attempts to shed light on the nature of the contribution of digital learning orientation (DLO), as an intangible resource, to the development of the dynamic capability of supply chain data analytics powered by artificial intelligence (SCDA-AI) as well as to the moderation of its effects on the enhancement of the operational capabilities of supply chain flexibility (SCFL), supply chain resilience (SCRE) and supply chain responsiveness (SCRES) in order to stabilize and improve supply chain performance (SCPER) in times of uncertainties and disruptions. The study was based on survey data collected from 200 foreign companies based in Morocco. Respondents were mainly senior and middle managers with experience in general management and supply chain (SC). Validity and reliability analyses and hypothesis testing were carried out using structural equation modelling (SEM) with SPSS Amos. The results revealed that DLO acts as an antecedent to SCDA-AI without moderating its effects on the three operational capabilities of SCFL, SCRE and SCRES. In addition, this study provides further empirical evidence that dynamic capabilities can produce significant results in terms of stabilizing and improving performance through the generation and/or reconfiguration of operational capabilities in situations of uncertainties and disruptions.

Keywords:
digital learning; supply chain; data analytics; capabilities; disruptions.

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1. Introduction

Given the rapid diffusion of information technology, big data has gained strategic importance and is recognized as one of the most valuable assets for many companies [1], [2], [3]. Big data includes heterogeneous formats and is characterized by its volume, variety, velocity, and veracity [4]. The accumulation of data has led many companies and supply chains (SCs) to develop analytical capabilities to transform this data into useful information that can improve decision making and support the performance of their SCs [5].

Supply Chain Data Analytics (SCDA) powered by artificial intelligence (AI) is one of the opportunities offered by the technological environment, which could be seized to generate unanticipated and unpredictable business value for both SCs and their partner companies [6]. To this end, SC partners are investing in the development of a dynamic capability dedicated to supply chain data analytics powered by artificial intelligence (SCDA-AI) in order to reduce costs and uncertainties, increase the effectiveness and efficiency of decision-making [7] and, ultimately, gain competitive advantage [8]. As such, accurate and timely data coupled with AI-driven data analytics could enhance the operational capabilities of supply chain flexibility (SCFL), supply chain resilience (SCRE), and supply chain responsiveness (SCRES) to respond to changes in customer requirements and needs and to risks and disruptive events in SC [9].

Furthermore, the literature on SCDA-AI capability has tended to focus on the technical dimension of the concept and its effects on SC process improvement. However, some studies have highlighted the importance of other complementary and intangible resources, particularly digital learning orientation (DLO) [10]. Indeed, the literature has largely focused on the direct role of DLO in collaborative development of SCDA-AI and performance improvement [11], [12]. These virtual mechanisms are even more important for the manufacturing sector due to its complexity and sensitivity to changes in customer requirements and disruptive events [12]. However, Marra et al. [13] point out that there is no evidence that digital technology in itself contributes to supply chain performance (SCPER).

This article responds to this call by describing the effects of SCDA-AI on SCFL, SCRE, SCRES and SCPER, as well as the direct and moderating effects of DLO on SCDA-AI's dynamic capability and its relationships with operational capabilities, through the reliance on organizational information processing theory (OIPT) and the dynamic capability view (DCV) as theoretical foundations. This being said, this paper attempts to shed new light on DLO as an antecedent resource to the development of dynamic capability of SCDA-AI and their respective contributions to the enhancement of the operational capabilities of SCFL, SCRE and SCRES, which should stabilize and improve SCPER in situations of uncertainties and disruptions. To this end, the present study attempts to answer the following research questions (RQs):

- RQ1. How does the intangible resource of DLO affect the development of the dynamic capability of SCDA-AI and its effects on the enhancement of the operational capabilities of SCFL, SCRE and SCRES?
- RQ2. How do the operational capabilities of SCFL, SCRE and SCRES influence SCPER in times of uncertainties and disruptions in manufacturing companies' supply chains?

In light of the above, the objectives of this study are to examine (1) the direct and moderating effects of DLO's intangible resource on the development of SCDA-AI's dynamic capability and its relationships with SCFL, SCRE and SCRES; (2) the direct effects of SCDA-AI's dynamic capability on strengthening the operational capabilities of SCFL, SCRE and SCRES; (3) the direct effects of SCFL, SCRE and SCRES capabilities on the stabilization and improvement of SCPER in situations of uncertainties and disruptions in SCs. Using survey data obtained from 200 foreign manufacturing companies based in Morocco, this study employs structural equation modeling (SEM) using SPSS Amos. As such, this study seeks to contribute to the literature by highlighting the importance of developing the dynamic and collective capability of SCDA-AI, as well as the intangible resource of DLO, in terms of dealing with changes in customer requirements and disruptive events and, consequently, their impact on strengthening the operational capabilities of SCFL, SCRE, and SCRES and, ultimately, on SCPER.

This document is organized into six sections. Following the introduction, section 2 presents the theoretical background. Section 3 presents the hypothesis development. The methodology is described in section 4. The results and their theoretical and managerial implications are presented and discussed in section 5. The main limitations and future directions of the research are announced in section 6.

2. Theoretical background

2.1 Organizational information processing theory (OIPT)

OIPT states that an organization evolves in a system, integrating several internal and external processes characterized by their complexity and uncertainty [14]. The theory provides a solid basis for explaining the organizational behavior of firms through the mechanisms of information processing. Gattiker and Goodhue [15] identified several sources of uncertainty, among them, instability in the SC environment, which requires more flexibility, resilience and responsiveness in the SC [16].

The increase in the volume of data managed by organizations implies an increased reliance on information processing, which requires the involvement of multiple internal and external entities [17]. This volume of data requires greater visibility to ensure effective decision making. According to Wong et al. [18], an organization's or SC's capability to deal with data could be initiated by an orientation of learning and inter-organizational sharing of mutually useful information to enhance the collaborative environment, reduce uncertainties, and mitigate disruptions. Premkumar et al. [19] argue that the lack of a learning and information processing orientation in an uncertain environment generates significant costs for organizations. Recent studies have shown that information processing capability, specifically SCDA-AI, improves performance and enhances a firm's competitive advantage [20].

2.2 Dynamic capability view (DCV)

DCV is a theoretical paradigm to better understand how firms develop competitive capabilities by adopting new technologies, including SCDA-AI [21]. In this regard, dynamic capabilities (DCs) also refer to an organization's ability to respond in a rapidly changing environment [22].

An important aspect of DCs is the presence of tools that can promote integrative learning mechanisms of endogenous knowledge. This helps promote DCs, which allows a firm to develop a competitive advantage [23]. DCs are strategically important for firms operating in a rapidly changing environment, where they need to react and adapt in a timely manner to a changing business environment [24]. In line with DCV, SCDA-AI, as a dynamic capability, modifies a company's resource base, operational routines and skills, particularly those relating to flexibility, resilience and responsiveness [25]. DCs have also been associated with tacit organizational elements, such as orientations, routines, processes, knowledge, and managerial knowledge [26]. According to DCV, the presence of a digital learning orientation, as an intangible resource, and SCDA-AI, as a dynamic capability, enables companies to anticipate, mitigate, and respond to changing customer demands and potentially disruptive events and ultimately gain competitive advantage through continuous reconfiguration of operational capabilities.

2.3 Digital learning orientation (DLO)

In the context of contemporary digital transformation, several studies have highlighted the relevance of digital literacy, digital ethics, and digital learning in building sustainable organizations and SCs [27], [28]. According to Graham [29], a learning orientation leads organizations to collaborate externally and be more cross-functional internally, which facilitates the sharing of useful information [30]. Furthermore, recent studies have shown that digital learning influences, primarily, intellectual openness, cognitive processes and strategies, and useful information-based knowledge [31].

However, despite the growing interest in this area of research, previous studies have exclusively examined the use of digital technologies and their results [32], [33], [34]. However, the present study aims to determine whether DLO would influence the development of the dynamic capability of SCDA-AI, while moderating its effects on SCFL, SCRE and SCRES, which ultimately impact SCPER in situations of uncertainty and disturbance.

2.4 Supply chain data analytics powered by artificial intelligence (SCDA-AI)

SCDA, enhanced by the use of cognitive technologies, in particular AI, helps to improve decisions about the complex processes of SC [35], [36]. In this respect, cognitive technologies enable machines to understand complex situations at high speed, process large amounts of data and interact like humans [37].

Today, it is imperative that companies and their SCs develop analytics capabilities to process the large volumes of data collected in real time in order to convert them into useful information and knowledge for achieving competitive advantage [38]. To this end, the joint use of cognitive technology (AI) and SCDA will enable more effective decision-making [39]. Also, AI technology has opened up many opportunities in supply chain management (SCM), especially process improvement, real-time responses to changing customer requirements, resource optimization, cost rationalization, and effective risk and disruption mitigation [40].

2.5 Supply chain flexibility (SCFL)

Companies are pursuing different strategies to achieve flexibility [41], some of which are investing in the development of SCDA-AI capability in order to achieve supply chain visibility and, consequently, minimize uncertainty by promoting rapid, informed decision-making [42]. It is also clear that manufacturing flexibility is essential to achieve responsiveness [43] and to respond quickly and effectively to internal and external changes [42]. In addition, efforts to enhance FSCL capability should extend beyond internal functional areas [44].

The literature has recognized that the development of SCFL capability is a costly investment, which should be undertaken with caution [45]. Recent studies have suggested that companies should perceive SCFL as a collective capability requiring an integrated effort on the part of SC partners. Indeed, this study perceives SCFL as the coordinated capability of SC partners to adjust, adapt and transform their resources and processes to cope with external dynamism.

2.6 Supply chain resilience (SCRE)

SCRE is an operational capability that allows a disrupted SC to recover and be more powerful than before [46]. Indeed, SCRE enables partner firms in a SC to cope with difficulties and adversities and to discern various opportunities in the business environment [47]. Furthermore, it is an indispensable ingredient of holistic risk management practices [47]. It is considered a long-term continuity element [48], creating a competitive advantage [47]. Indeed, members of an SC are responsible for building resilience in their organization and promoting the resilience of the entire system [47]. Due to the increasing exposure to SC risks, there is an increased focus on the need to improve SCRE capability [49].

2.7 Supply chain responsiveness (SCRES)

SCRES is the ability to respond to immediate or sudden market dynamics [50]. In other words, SCRES is a company's ability to respond effectively and rapidly to changing customer needs and requirements [51]. In this respect, a company's ability to be responsive also depends on its SC partners and their collective efforts [52]. According to Singh [53], the level of SCRES is measured by the speed with which the SC can modify its production within the range of the four types of external flexibility, in particular product, volume, combination and delivery, in order to respond to external stimuli [54]. Indeed, SC must be able to meet challenges pertaining to reducing manufacturing and delivery times, shortening product life cycles, and improving product variety [55]. Thus, responsiveness is considered one of the operational capabilities that enable SCs to gain competitive advantage [56].

3. Hypothesis development

Figure 1 presents our research model.

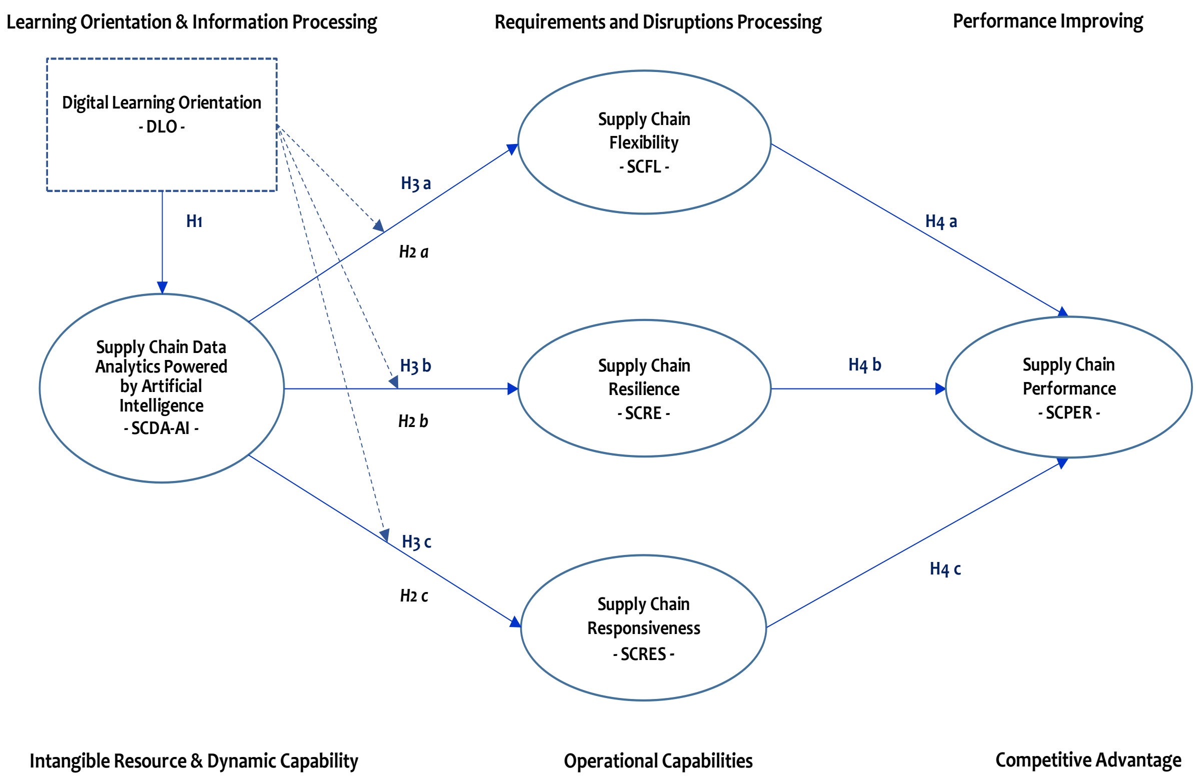

Fig. 1. Research Model

3.1 Direct effect of the DLO

Companies and SCs focused on learning are always looking to improve their processes by adopting effective ways of organizing themselves into cross-company and cross-functional teams [57]. Learning capability is an intangible resource antecedent to any collaborative development of dynamic and/or operational capabilities, enabling the effective and efficient management of changing customer requirements and needs, as well as the mitigation of resulting disruptions [29].

Therefore, it is hypothesized that:

H1. DLO has a positive effect on SCDA-AI.

3.2 Moderating effects of DLO

The focus on learning leads CS partner organizations to collaborate externally and be more cross-functional internally, to facilitate the sharing of useful information and new knowledge [30]. In order to keep learning up to date, information needs to be systematically reassessed and structured, particularly that inherent in customer requirements and needs and potential disruptions, thereby continuously enhancing SCFL, SCRE and SCRES capabilities [57], [3].

Therefore, it is hypothesized that:

H2a. DLO positively moderates the relationship between SCDA-AI and SCFL.

H2b. DLO positively moderates the relationship between SCDA-AI and SCRE.

H2c. DLO positively moderates the relationship between SCDA-AI and SCRES.

3.3 Direct effects of the SCDA-AI

SCDA-AI and SCFL

SCDA-AI can be effectively used to cope with uncertainties in SCs by changing the level of SCFL. Also, SCDA-AI improves SCFL, which results in improved performance [58], [59]. In addition, the development of dynamic capability of SCDA-AI is necessary to meet the SC's needs for flexibility and responsiveness. According to Gawankar et al. [60], SCDA-AI would mitigate decision-making inefficiencies as well as several obstacles to SCFL caused by the bullwhip effect in the SC. Therefore, in a disruptive and highly volatile situation, SCDA-AI is strongly linked to SCFL.

Therefore, it is hypothesized that:

H3a. SCDA-AI has a positive effect on SCFL.

SCDA-AI and SCRE

Previous studies on SCM have highlighted the importance of SCDA-AI for its positive effect on organizational performance [61]. However, the role of SCDA-AI in enhancing SCRE has not been sufficiently examined by the literature. In addition, some studies have shown a positive relationship between SCDA-AI and SCV [17]. Recently, Dubey et al. [62] argued that SCDA-AI has a direct and positive effect on SCRE. To this end, investment in developing SCDA-AI capability leads to improved SCV and, consequently, improved SCRE [63], [64], [65].

Therefore, it is hypothesized that:

H3b. SCDA-AI has a positive effect SCRE.

SCDA-AI and SCRES

In an uncertain and dynamic environment in terms of changing customer requirements and needs, quick action is needed to deal with these changes, which is only possible by developing SCDA-AI, as an environmental information processing capability [66]. SCDA-AI extracts information that can be useful in making decisions about new and non-standard customer requirements. SCRES capability aims to reduce manufacturing flow and transport/distribution time [67]. To this end, SCDA-AI makes it possible to build a responsive SC, facilitating optimized positioning of key resources and actors (suppliers, carriers, distributors), in order to gain a competitive advantage

Therefore, it is hypothesized that:

H3c. SCDA-AI has a positive effect on SCRES.

3.4 Direct effects of the SCFL, SCRE and SCRE

SCFL and SCPER

The SCM literature has recognized that SCFL contributes to the achievement of performance objectives [68]. As such, Chirra et al. [69] have emphasized that SCFL is necessary for companies to improve their SCPER. Other studies have pointed out that SCDA-AI acts as a catalyst for SCFL, which would lead to SCPER improvement. Consequently, Tseng et al. [70] found that SCFL as well as the quality of information created and shared are among the main criteria influencing SCPER.

Therefore, it is hypothesized that:

H4a. SCFL has a positive effect on SCPER.

SCRE and SCPER

This research argues that the SCRE should be supported by the SCDA-AI to mitigate disruptive risks, and this to ensure a stabilization of the SCPER level [71]. The negative impact of disruptions in SC could be avoided by enhancing SCRE capability, enabling a return, within a desirable timeframe, to the favorable performance level after the impact of a disruptive incident [72]. However, other research has demonstrated a favorable association between SCRE and various performance dimensions [47], [73]. Therefore, it is hypothesized that:

H4b. SCRE has a positive effect on SCPER.

SCRES and SCPER

SCRES capability is an essential element for companies to meet changing global market demands and, as a result, withstand global competition [74]. As such, high levels of SCRES enable companies to respond better to customer needs than their competitors. Also, some previous studies have examined the essential role of SCRES in improving company and market performances [51]. Therefore, it is hypothesized that:

H4c. SCRE has a positive effect on SCPER.

4. Research methodology

4.1 Data collection

In this study, the target sample was made up of managers of foreign manufacturing companies located in industrial acceleration zones in Morocco. These managers were targeted because they belong to companies that are partners in global value chains (GVCs), which often face a high degree of uncertainty, adverse conditions and risks of disruption [47]. To this end, the database of the Ministry of Industry and Trade was exploited to carry out an online survey in 2023 to test the hypotheses. The initial sample included informants involved in the general management and SCM. After eliminating mailing errors, the sample included 765 contacts. At the end of the survey period, 200 completed questionnaires were received by the respondents, a response rate of 26.1%. This is, in effect, a medium sample size [75] and a number of observations greater than the free parameters of the model which is a necessary condition for identifying a structural model [75]. Table 1 presents the profiles of the respondents to this survey.

Table 1. Respondents' Profile Summary

Structure of the sample	**Frequency**	**Valid %**
Firm size:		
Less than 100 employees;	50	25%
101 to 200 employees;	15	7.5%
201 to 300 employees;	45	22.5%
More than 300 employees.	90	45%
Manufacturing industry type:		
Automotive industry;	60	30%
Aeronautics and aerospace industry;	53	26.5%
Food industry;	35	17.5%
Pharmaceutical industry;	25	12.5%
Electronic and electrical components industry;	15	7.5%
Rubber and plastic products industry.	12	6%
Nationality of respondent companies:		
Spanish companies;	50	25%
French companies;	43	21.5%
German companies;	31	15.5%
Portuguese companies;	30	15%
Japanese companies;	26	13%
American companies.	20	10%

Structure of the sample	Frequency	Valid %
Respondent designation:		
Top management;	95	47.5%
Middle management;	83	41.5%
Lower management.	22	11%
Respondent experience:		
Less than 3 years;	18	9%
3 to 5 years;	32	16%
6 to 9 years;	63	31.5%
More than 9 years.	87	43.5%
Total	**200**	

4.2 Measurement model

The survey instrument used a seven-point Likert scale (1-strongly disagree and 7- Strongly agree). The measurement items for the theoretical constructs in the research model are adapted from prior studies. This approach allows for the development of formative and composite measures in the context of this study. Therefore, the measurement items can affect the construct with which they are affiliated and which they measure. The measurement items used in this study are presented in Table 2.

The dynamic capability of the SCDA-AI was operationalized by four items adapted from the scale of Srinivasan and Swink [17] and Dubey et al. [20]. The operational capability of SCFL was operationalized by four items adapted from the scale of Rojo et al. [76] and Juan et al. [77]. The operational capability of SCRE was operationalized by four items adapted from the scale of Dubey et al. [62]. The operational capability of SCRES was operationalized by four items adapted from the scale of Qrunfleh and Tarafdar [51] and Williams et al. [42]. The intangible resource of DLO was operationalized by three items adapted from the scale of Iyer et al. [57]. SCPER was operationalized by four items adapted from the scale of Wamba et al. [78] and Gu et al. [79].

Table 2. Measures, reliability, and validity.

Measures	Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Ext. (AVE)
Supply Chain Data Analytics Powered by Artificial Intelligence (adapted from: Srinivasan & Swink [17]; Dubey et al. [20]):		0.937	0.910	0.719
SCDA-AI1. Use of advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision-making.	0.831			
SCDA-AI2. Use of multiple data sources to improve decision-making.	0.865			
SCDA-AI3. Use of data visualization techniques (e.g., dashboards) to assist decision-maker in understanding complex information.	0.926			
SCDA-AI4. Deployment of dashboard applications/information in communication devices (e.g., smart phones, computers) of the supply chain processes.	0.934			
Supply Chain Flexibility (adapted from: Rojo et al. [76]; Juan et al. [77]):		0.884	0.838	0.571
SCFL1. Our supply chain can adjust manufacturing facilities, processes and operations.	0.845			
SCFL2. Our supply chain can rationalize through information systems the management of transport and distribution.	0.786			
SCFL3. Our supply chain can adjust its delivery lead times.	0.837			
SCFL4. Our supply chain can adjust its size of orders.	0.772			
Supply Chain Resilience (adapted from: Dubey et al. [62]):		0.806	0.859	0.612
SCRE1. Our supply chain can easily restore the flow of materials.	0.845			
SCRE2. Our supply chain would not take long to recover normal operating performance.	0.973			
SCRE3. Our supply chain would quickly recover to its original state.	0.665			
SCRE4. Our supply chain can quickly deal with disruptions.	0.500			

Measures	Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Ext. (AVE)
Supply Chain Responsiveness (adapted from: Qrunfleh & Tarafdar [51]; Williams et al. [42]):				
SCRES1. Our supply chain is able to handle difficult nonstandard orders.	0.627	0.778	0.827	0.549
SCRES2. Our supply chain is able to produce products characterized by numerous features options, sizes and colors.	0.695			
SCRES3. Our supply chain is able to adjust capacity so as to accelerate or decelerate production in response to changes in customer demand.	0.500			
SCRES4. Our supply chain is able to introduce large numbers of product improvements/variation.	0.792			
Digital Learning Orientation (adapted from: Iyer et al. [57]):				
DLO1. Our supply chain sees digital learning as an investment rather than an expense in the age of big data.	0.775	0.767	0.847	0.649
DLO2. Digital learning capability is essential for improving our supply chain processes in the era of massive data.	0.837			
DLO3. We have specific mechanisms for the digital sharing of useful information and knowledge learned in supply chain processes in the era of big data.	0.571			
Supply Chain Performance (adapted from: Wamba et al. [78]; Gu et al. [79]):				
SCPER1. We were able to save more on operating costs.	0.851	0.891	0.882	0.651
SCPER2. We can achieve a better return on investment.	0.783			
SCPER3. We are able to achieve shorter lead times.	0.776			
SCPER4. We are able to meet customers' diversified product requirements	0.777			
Fit indices: x2/df (chi-square) = 457,430 / 216 = 2.118, standardized root mean square residual (SRMR) = 0.0664, root mean squared error of approximation (RMSEA) = 0.074, Tucker-Lewis's index (TLI) = 0.912, comparative fit index (CFI) = 0.925.				

4.3 Nonresponse bias and common method bias

For testing nonresponse bias, the answers of the firms that quickly respond to participate in the survey and enterprises that accept late were compared by means of t-test. There were no statistically significant differences between early and late responses.

To examine the potential threat of variance bias in the common method, a one-factor test was recommended [80]. The relevant factor analysis revealed that neither a single factor emerged, nor was a general factor identified in the unrotated factor structure. Additionally, in this study, to examine common method bias, the correlation relationships between the constructs were investigated. When the correlation between concepts is less than 0.90, the bias of the common method is accepted [81]. As shown in Table 3, the correlations between concepts in this study are below 0.90.

Table 3. Inter-construct correlation estimates and related AVEs

	SCRE	SCDA-AI	SCFL	SCRES	SCPRE	DLO
SCRE	**0.782**					
SCDA-AI	0.693	**0.848**				
SCFL	0.737	0.707	**0.756**			
SCRES	0.691	0.662	0.704	**0.741**		
SCPER	0.680	0.652	0.694	0.650	**0.807**	
DLO	0.561	0.537	0.572	0.536	0.528	**0.805**

Note: The values on the diagonal (in bold) represent the square root of average variance extracted (AVE) for each factor, while the variables below the diagonal represent the correlations between each pair of factors.

4.4 Data analysis technique

Confirmatory factor analysis (CFA) using SPSS Amos 22 was done to validate the factor structure of variables under the focus of this study and assess the validity and reliability of the measurement models corresponding to each construct in the research model (Figure 1). CFA is an appropriate tool because the associations between the proposed items and constructs have been specified. In addition, SEM is useful for examining causal relationships and dealing with multiple dependent variables as well as the error terms of all dependent and independent variables in a structural model [75]. Similarly, SEM facilitates the examination of the overall causal fit of a holistic model as well as moderation effects.

4.5 Reliability and validity

The measurement model was evaluated on the basis of the reliability of the internal consistency and the converging validity of measurements associated with the constructs and the discriminant validity. Internal consistency reliability was tested by Cronbach's α ($\alpha > 0.767$) and composite reliability (CRs > 0.827), the results of which verified acceptable internal consistency. Convergent validity was assured, as all the loadings were similar to or greater than 0.5, with acceptable average variance extracted (AVE) values (AVEs > 0.549), as displayed in Table 2. The discriminant validity was verified if the shared variance between the latent variable and its indicators (AVE) was greater than the variances (squared correlation) of each variable with the other latent variables [82], as displayed in Table 3.

In addition, CFA analysis was done to validate the factor structure of variables under the focus of this study. Kline’s [83] recommendations on several statistical parameters were used to evaluate the model’s goodness of fit (chi-squared/degrees of freedom: $\chi 2/df < 3$, Tucker–Lewis’s index: TLI > 0.90, comparative fit index: CFI > 0.90, root mean square error of approximation: RMSEA < 0.10 and standardized root mean square residual: SRMR < 0.09. The hypothesized six-factor measurement model had a satisfactory fit (x2/df = 457,430 / 216 = 2.118, $p < 0.001$, SRMR = 0.0664, TLI = 0.912, CFI = 0.925, RMSEA = 0.074), as displayed in Table 2.

5. Results and discussion

5.1 Main results

This study used bootstrapping with 5,000 samples to determine the appropriateness of the path coefficients. Based on the statistical results obtained, with the exception of three moderation hypotheses H2a (SCDA-AI*DLO → SCFL), H2b (SCDA-AI*DLO → SCRE), and H2c (SCDA-AI*DLO → SCRES), the rest of the research model hypotheses were well supported. The standardized correlation coefficients are presented in Table 4 and Figure 2.

Table 4. Results of the path analysis and hypothesis testing

Causal Path				Estimate	S. E	P	Support
H1	DLO	→	SCDA-AI	0.151	0.129	*	Yes
H2a	SCDA-AI*DLO	→	SCFL	-0.176	0.032	ns	No
H2b	SCDA-AI*DLO	→	SCRE	-0.302	0.038	ns	No
H2c	SCDA-AI*DLO	→	SCRES	-0.142	0.041	ns	No
H3a	SCDA-AI	→	SCFL	0,824	0.053	***	Yes
H3b	SCDA-AI	→	SCRE	0.443	0.050	***	Yes
H3c	SCDA-AI	→	SCRES	0.653	0.065	***	Yes
H4a	SCFL	→	SCPER	0.368	0.098	***	Yes
H4b	SCRE	→	SCPER	0.146	0.090	*	Yes
H4c	SCRES	→	SCPER	0.426	0.125	***	Yes

Notes: S.E: Standard error; *** p<0.001; * p<0.1 and ns: non-significant.

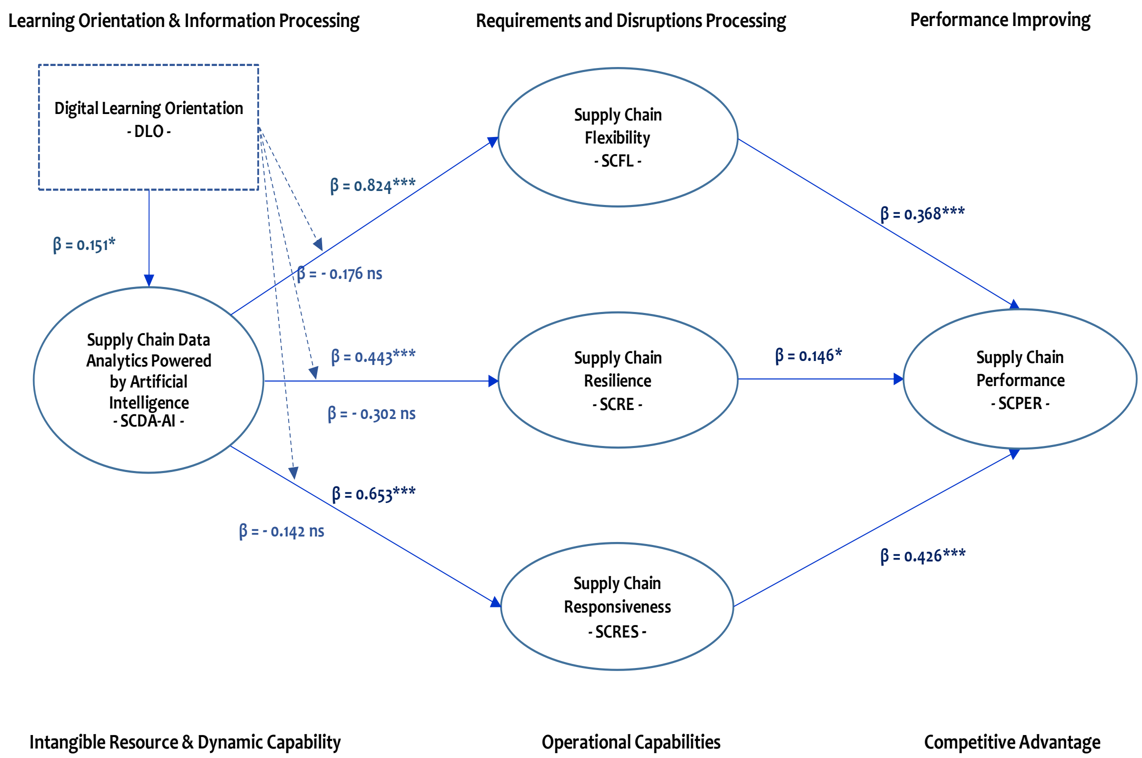

Fig. 2. Final SEM Model.

5.2 Theoretical implications

This study used OIPT to understand how the intangible resource of DLO could moderate the direct effects of SCDA-AI on the enhancement of operational capabilities of SCFL, SCRE and SCRES in times of uncertainty and disruption, and address the fact that DVC is inappropriate to explain the antecedents of SCDA-AI development as a dynamic capability. Indeed, the present study is one of the first to test the relationships between an intangible resource (DLO), a dynamic capability (SCDA-AI), three operational capabilities (SCFL, SCRE and SCRES) and SCPER.

Furthermore, the results obtained revealed that DLO acts, in line with the results of the study conducted by Iyer et al [57], as an antecedent to the development of SCDA-AI capability. However, this study did not demonstrate the moderating effect of DLO on the relationships between the dynamic capability of SCDA-AI and the operational capabilities of SCFL, SCRE and SCRES, in contrast to the studies carried out by Iyer et al [57] and Benzidia et al [3].

In addition, this study provided further empirical evidence that the dynamic capability of SCDA-AI can produce excellent results in terms of enhancing operational capabilities, particularly SCFL, SCRE and SCRES, following the example of studies conducted by Fernando et al [58], Edwin Cheng et al [59], Dubey et al [62] and Abdelkafi and Pero [66].

Furthermore, the present study has demonstrated that the three operational capabilities do indeed have direct and positive effects on SCPER, which is comparable to the results announced by the studies carried out by Chirra et al [69], Tseng et al [70], Gölgeci and Kuivalainen [47], Belhadi et al [73] and Qrunfleh and Tarafdar [51].

5.3 Managerial implications

The results of this study provide guidance to managers exploiting analytical capabilities to extract information useful for decision-making in the management of complex SC networks. In this regard, SC partners are investing in the implementation of this SCDA-AI collaborative capability, without any assurance of positive results. Indeed, the results obtained suggest that DLO is an antecedent to the development of SCDA-AI, as a higher-order dynamic capability, with positive effects on enhancing the operational capabilities of SCFL, SCRE and SCRES. Consequently, the presence of DLO's intangible resource encourages SC managers to develop SCDA-AI in order to achieve the desired results, in an environment marked by uncertainties in demand and supply and the resulting disruptions.

In addition, the results inspire SC managers and policy-makers alike on the important role that Big Data analytics capability (SCDA) and cognitive technology (AI) jointly play in mitigating uncertainties and disruptions. These findings are explicit and particularly useful for manufacturing sector decision-makers. In addition, they provide guidance to managers engaged in the implementation of SCDA-AI on how this capability enhances operational capabilities, particularly SCFL, SCRE and SCRES, and their contribution to improving SCPER in times of uncertainties and disruptions.

Finally, the results confirm that SC partner companies need to undertake collaborative efforts to develop high-order dynamic capability of SCDA-AI in order to strengthen other operational capabilities dedicated to SCFL, SCRE and SCRES and, ultimately, to mitigate supply and demand uncertainties and related disruptions.

6. Conclusion

Supported by OIPT and DCV, this study examines the interactions between the intangible resource of DLO, the dynamic capability of SCDA-AI and the operational capabilities of SCFL, SCRE and SCRES, as well as their respective contributions to the stabilization and improvement of SCPER. In this respect, the main results show that DLO is indeed an antecedent of SCDA-AI without, however, having a moderating effect on the enhancement of SCFL, SCRE and SCRES capabilities by SCDA-AI.

In addition, SCDA-AI capability has a positive impact on the three operational capabilities of SCFL, SCRE and SCRES, enabling companies and SCs to cope with supply and demand uncertainties and the resulting disruptions. Furthermore, it appears that SCFL and SCRES capabilities have relatively strong positive effects on SCPER compared with SCRE, demonstrating the stabilizing or improving performance role played by each of the three operational capabilities.

Some limitations could be raised for this study. Firstly, this study used cross-sectional data to test the research hypotheses. Indeed, it seems difficult to assess causality between hypothesized relationships using this type of data. Therefore, a longitudinal study is highly recommended to comprehensively address unanswered questions related to causality and common method bias. Secondly, this study tested a research model incorporating six constructs: one intangible resource (DLO), one higher-order dynamic capability (SCDA-AI), three operational capabilities (SCFL, SCRE and SCRES) and a single performance perspective (SCPER). However, other types of resources and capabilities, as well as performance perspectives and dimensions, can be studied to further explain their collective interactions in terms of performance improvement. Thirdly, this study did not take into account other dimensions and perspectives of performance, particularly the financial dimension and the organizational perspective, in order to inform managers of companies and SCs about the trade-off to be made between the financial cost of investing in SCDA-AI capability and the expected gain in terms of performance. Fourthly, for reasons of generalizability and simplicity, data have been consolidated for all manufacturing activities. However, the results may differ according to the type of industry and service companies. Finally, SCDA capability should be explored in relation to AI in future research, making the research model more comprehensive and integrated for researchers and practitioners.

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Enhancing project quality through effective team management

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Enhancing project quality through effective team management

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Abstract:
This study aims to explore the relationship between team management and project quality, identify key contributing factors, and examine the role of employee involvement, commitment, and innovation. An empirical, cross-sectional study was conducted using an online survey to gather data from 510 respondents across various industries, projects, and experiences. Data analysis employed statistical techniques to reveal patterns and trends. Key factors contributing to project success include communication, comprehensive planning, clear roles and responsibilities, stakeholder requirements, and a supportive work environment. The significance of proper management approaches, techniques, and attitudes was also highlighted. The findings contribute to the current body of knowledge on project quality management and emphasize the need for a human-centered management approach to achieve high-quality project outcomes. This study sheds light on the pivotal role of effective team management in project quality, providing valuable insights and recommendations for project managers, team leaders, and organizations seeking to improve project performance.

Keywords:
team management; project quality; leadership competencies; human-centered approach; employee involvement.

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1. Introduction

In today's competitive business landscape, project quality is of utmost importance as organizations strive to meet the ever-evolving needs of their clients [1]. Quality orientation has its economic justification. While in the 1970s, quality costs were estimated at up to 30% of revenues [2], at the beginning of the 21st century, they amounted to 5-10% of revenues [3]. Reducing quality costs in projects is particularly difficult because it requires very good planning and performing tasks right the first time. Achieving this relies heavily on the effective management of teams, which are at the heart of driving innovation, ensuring efficiency, and fostering a culture of excellence [4]. As such, understanding the critical relationship between effective team management and project quality has become essential for project managers, team leaders, and organizations aiming to consistently deliver high-quality results [5].

Quality management in project management is acknowledged as a distinct domain, emphasizing planning, assurance, and quality control [6]. This ensures that project requirements are fulfilled by establishing strong stakeholder relationships and adhering to quality standards. However, the connection between team and project quality management remains ambiguous in existing literature [1], [7]. Contemporary organizations recognize that project quality is determined by both the outcomes and the methods employed to achieve them. Basu highlighted three facets of project quality: product quality, management process quality, and organizational quality (e.g., leadership, skills, and communication). Other scholars propose that quality comprehension varies according to the project phase, introducing notions such as design quality and process quality [7]. Consequently, project quality can be characterized as the capacity to produce results that satisfy stakeholder requirements and expectations by combining the quality elements related to organization, design, and process [8].

Effective team management ensures that project teams develop a quality management policy and focus on quality control, meeting customer requirements and stakeholder needs [1], [4]. This involves creating a performance-oriented culture emphasizing continuous improvement, clear goals, and competent task delegation [1], [9]. Effective team management also involves fostering inter-organizational cooperation, utilizing quality management tools and methods, and providing top management support for quality management practices [10]. Furthermore, teams should be assessed for their capability to undertake tasks and employ quality assurance processes, risk management plans, and the expertise of team members [11].

The existing literature has extensively investigated the variables influencing a team's performance. Nevertheless, the association between these variables and the attainment of project quality remains ambiguous. This can be attributed to the intricate interplay between team and quality management domains [12]. Moreover, the unique constraints imposed by the temporary nature of project implementation further complicate the applicability of a substantial portion of quality methodologies typically employed in industrial or service-based contexts.

The primary objectives of this article are to provide a comprehensive understanding of the relationship between team management and project quality. Specifically, the aim is to address the following research questions:

- How does effective team management contribute to enhancing project quality?
- What are the key factors in team management that influence project quality?
- How can different team management practices impact employee involvement, commitment, and innovation in projects?

By exploring these research questions, we aim to investigate the connection between effective team management and project quality across various industries and organizations and seek to identify the key factors and practices in team management that significantly contribute to high-quality project outcomes. Additionally, the role of employee involvement, commitment, and innovation in enhancing project quality through effective team management will be examined.

This article has the following sections: literature review, methodology, results, discussion, and conclusions. The literature review synthesizes existing research, followed by the methodology that details our study's approach. The results section presents findings, while the discussion elaborates on their implications. Finally, the article concludes with a summary and recommendations for future research and practice.

As projects become increasingly complex and diverse, the need for cohesive and high-performing teams to deliver high-quality results is more critical than ever [13]. Project managers and team leaders need to understand and adopt the best practices in team management, as this can ultimately determine the success or failure of their projects [14]. The findings and recommendations in this article can serve as a valuable resource for researchers and project managers seeking the best practices for their teams and projects, ultimately leading to higher-quality results and project success.

2. Literature review

Quality is achieved thanks to people, their attitudes, and their commitment [15]. Many scientific publications and those popularizing pro-quality approaches focus on implementing methods and techniques [1]. However, without the involvement of employees, management, consultants, and the board of directors, the tools will not bring the intended results [16]. This will not be changed even by the advent of quality 4.0, despite the extensive use of computer applications, machine learning, and artificial intelligence. The tools and technical skills are necessary. However, studies show that soft skills are more important for the project's success [17].

Many publications have been devoted to project team management principles, methods, and techniques. What is lacking, however, is a clear link between activities aimed at creating and managing project teams and the effects in the form of the project quality and the quality of its results [10], [18], [19]. Studies show that the sources of project failures should not be sought in technological problems, but they are primarily sociological, related to mistakes made at various stages of project team management [20], [21]. One of the most common excuses for omitting quality-related activities in a project is time pressure, and such an approach has a disastrous effect on the quality of the design, process, and results [22, p. 17]. The level of innovation, commitment, and quality can also be limited by different values shared by employees and the organization, dehumanization, accusing of making mistakes, searching protection against potential liability for errors, lack of a holistic view, unclear roles and expectations, lack of explanation of the reasons, "command and control" approach [23, p. 53]. The analysis of publications, research results, case studies, and practical experience show that the most important quality factors in a project team are based on planning pro-quality activities, awareness of the goals, needs, and expectations of stakeholders, team structure tailored to the needs, proper division of roles and responsibilities, respecting the decision-making chain, procedures and policies to improve the efficiency of operations and decision-making, tools supporting efficient work, ensuring an even pace of work (flow), and feedback [23].

Achieving high-quality results by the team requires, among others, commitment, cooperation, openness, and trust [15], [24]. In some cases, a project-oriented and collaborative mindset may be more critical than those competencies that can be acquired quickly. This was confirmed, for example, by research conducted in teams implementing projects at Google [25].

One of the best-known models of creating and managing a project team is the B.W. Tuckman model from the 1960s, which distinguishes forming, storming, norming, and performing. Research conducted in recent years shows that nowadays, the actual life cycle of a project team increasingly deviates from this pattern. The much higher dynamics of today's projects mean that the storming phase often occurs throughout the project implementation period [26]. Other research shows that this model does not work in virtual teams, where the volatility of team members is much higher, and it often becomes necessary to return to previous phases [27, p. 57]. Researchers also emphasize the non-linearity of team development, which is influenced by external factors, including time pressure [28, p. 22].

The importance of virtual teams has increased during the pandemic. They are currently used in many projects to streamline work and reduce costs. New challenges related to virtual teams are still being explored. However, it is already known that managers of these teams face difficulties related to effective communication, knowledge sharing, trust building, and working conditions conducive to cooperation [29]. This forces a different approach to building and managing teams.

Competencies, understood as an employee's ability to use their knowledge, skills, and experience in a professional situation to solve problems, are a crucial resource that enables the achievement of project objectives [30, p. 17]. Therefore, managers should strive to create teams with diverse competencies covering all areas of project activities. Such cross-functional teams have the potential to achieve better results thanks to the ability to apply more solutions and combine them creatively. The world of VUCA (volatility, uncertainty, complexity, and ambiguity) surrounding projects makes it impossible to manage quality mechanically using a fixed set of basic tools and techniques today. Quality-related competencies necessary to work in a project team include primarily those that increase efficiency, including situational orientation, memory, meta-cognition (i.e., cognition based on indirect premises), the ability to recognize repetitive patterns, efficient decision making, troubleshooting, mental flexibility and creativity, group work, communication, expert skills, resistance, and critical thinking [31, p. 29].

Competencies related to quality should enable teams to prevent biases in projects that may arise due to over-optimism, mistakes during planning, anchoring to suboptimal technologies, methods, approaches, cognitive dissonance, and limitations in accepting proposals that go beyond accepted standards. It should also prevent biases related to loss aversion towards expenses already incurred (sunk costs), limiting the field of view, omitting broader aspects of the project, and prejudice within the group or towards the environment. [32, p. 97]. Young, inexperienced project managers are especially prone to this mistake [17]. An additional difficulty for them may be the lack of support and inappropriate culture of the organization where the project is implemented [33].

High competencies of team members enable increasing their autonomy. Research shows that this improves the quality of long-term decisions and increases commitment and cooperation [33]. It should be emphasized that these competencies should be adapted to the project's specificity. Therefore, competence needs should be diagnosed already at the recruitment stage [34].

The increasing complexity of the environment and the resulting limited predictability and high volatility mean that managers of even small projects face significant and unexpected obstacles [35]. The possibility of obtaining support from a team with diverse competencies, experience, and different viewpoints can significantly help overcome problems. Therefore, the modern project manager striving to achieve high-quality results and good project management should avoid the "command and control" approach and instead demonstrate leadership behavior [36], [37].

Complexity in projects results mainly from the behavior of stakeholders, the behavior of systems that are the object of design work or their background, and the lack of clarity. It can refer to four main areas: structure, methodology, concept, and changeability over time [32, p. 39]. A complex project manager should use leadership skills to build a team to reduce complexity and accomplish things [27, p. 49]. Project leaders' most desirable leadership competencies include [38] coordination instead of control, availability for subordinates, ensuring the right amount of information, providing feedback, fairness, decision-making ability, sincerity, focus on individual development, team building, and respect.

Leadership behavior in projects, especially complex ones, requires an individual approach and planning. Due to the temporary nature of projects, the high competence of employees, and the complex environment, leaders rarely exceed the knowledge and skills of all team members [39]. The expectations of employees are also changing, especially those from the Y and Z generations. They expect more significant participation in management, but in return, they offer commitment and a creative approach to solving problems [40].

3. Methodology

Prior research in project quality management has been characterized by a disjointed approach, concentrating on particular standards, methodologies, approaches, or techniques. Comprehensive investigations demonstrating how project managers and team members handle quality multidimensionally are scarce. Dialogues with experienced project managers and literature reviews indicate that quality is frequently not regarded as a vital component of project management. In-depth research on attitudes toward quality in projects has been largely absent. The findings discussed in this article are part of an extensive research program dedicated to project quality management. Given the wide-ranging nature of the research, individual topics are addressed in distinct articles.

The research was conducted in October and November 2022, targeting project managers and team members. The research sample's selection criteria ensured a diverse spectrum of industries, projects, and experiences (Fig. 1). Criteria for differentiating respondents included project size, competencies, organizational size and location, and industry.

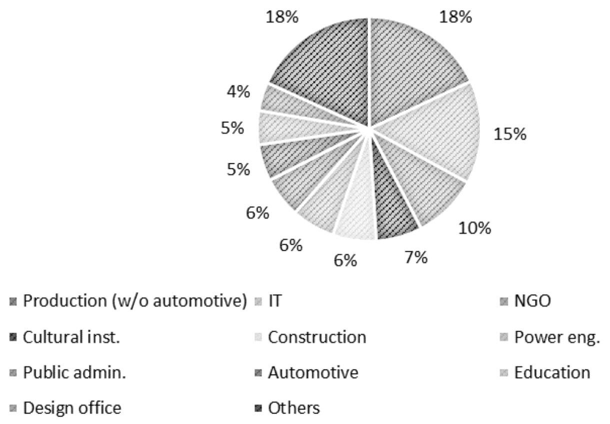


Fig. 1. Structure of organizations participating in the study

The study centered on participants' perceptions of quality. Due to the extent of the research, the number of questions, and the anticipated number of participants, an online questionnaire-based survey was selected as the research instrument (see Appendix A). The survey comprised 17 questions concerning requirements management, respondent demographics, projects, and organizations.

To reduce respondent discouragement, four types of questions were employed: ranking, 7-point scale questions, yes/no questions, and open-ended questions. The ranking question is more labor-intensive for the respondent but allows showing the preferred order of answers. This type of question allows for a deeper examination of respondents' preferences when the answers are related, e.g., questions about the competencies of managers and team members. The 7-point scale was used in relation to questions examining the preferences of respondents when the relation between individual answers was not crucial, e.g., a question about a manager's influence on motivation. In turn, the yes/no questions were used to find whether the specific phenomena exist in the organization, e.g., questions about phases of team building.

A potential risk in survey research is the restricted ability to validate the answers provided. Verification techniques involved analyzing completion time, comparing responses from participants within the same organization, and examining response patterns. In the case of answers given much faster than average, respondents were asked to explain this and, in some cases, to complete the survey again. With regard to yes/no questions, it was possible to compare the answers given by employees of the same organization. Contradictory answers were explained to respondents. The scripts analyzing the answers have been programmed to detect situations when the respondent marked the same value in all responses, which suggested using the answer template without analysis. In a few rare instances of dubious responses, participants were requested to complete the questionnaire again.

The analysis of the results was conducted using custom Python scripts and spreadsheets. The following packages were utilized: *scipy.stats, scipy.spatial, pingouin, scikit_posthocs, math, statistics, pandas*. The length of scripts exceeds 3,000 lines of code. The results of scripts were presented in the form of large arrays with over 100 columns, which were further analyzed using spreadsheets. Therefore, this paper will present them in a processed form of figures and descriptions. L. Cronbach's Alpha coefficient was employed to assess the survey's internal consistency, yielding a value of 0.8777, which surpasses the recommended minimum of 0.8. The coefficient was calculated using the *cronbach_alpha* function of the *pingouin* package for all the questions except demographic ones [41].

As most questions employed an ordinal scale, non-parametric statistical techniques and measures were chosen for analysis and interpretation, including median, absolute deviation of the median, Spearman's rank correlation coefficient, Chi2 test, Mann-Whitney U test, Shapiro-Wilk distribution test, Kruskal-Wallis test, Dunn test, Kendall's W coefficient, and cosine similarity measure [42]–[47]. The use of non-parametric statistics constrains the presentation of results.

4. Results

4.1 Sample

The survey garnered participation from 510 respondents across more than 170 organizations. The gender distribution was somewhat biased towards male respondents (51%), with two participants opting not to reveal their gender. Women were more commonly involved in projects with smaller budgets. In projects exceeding €500,000, women constituted 35%, while in other categories, they accounted for 50-60%. This discrepancy can be ascribed to the educational background and the nature of the projects examined. Large-budget projects were mainly associated with engineering industries, where women comprised approximately 30% of individuals with engineering education. Female respondents were predominantly found in organizations related to public administration, education, non-governmental organizations, culture, and financial services. Men were more prevalent in the construction and information technology (IT) industries.

Nearly 70% of respondents were aged between 26 and 45 years. Almost half possessed a total professional experience of up to 10 years; an additional 32% had up to 20 years. Project work experience was generally shorter, with 79% of respondents having no more than ten years. Although project management has been evolving for several decades, organizations have only recently started to concentrate on project-based approaches. There has been a recent trend toward treating conventional processes as projects, which is more prevalent among public administration representatives, possibly due to the implementation of EU-funded projects.

The survey targeted both project managers and team members. Some respondents occupied multiple roles across various projects, with 43% indicating they were managers in at least one project. Nearly 90% of respondents held a higher education degree, 9% had secondary education, and about 1% had a PhD or higher degree. The most prevalent fields of education were technical (42%), economic and managerial (32%), humanities (7.5%), and IT (5.3%). Respondents also reported backgrounds in pedagogy, sociology, administration, law, and other fields.

Over 170 organizations were represented in the survey. Among the surveyed teams, 35% had no more than five members, and 39% had up to 10 members. The industry and nature of the project primarily influenced team size. A statistically significant relationship was discovered between budget and team size, but only for teams with up to 20 members ($p=0.003$). Larger teams were more prevalent in large and very large organizations.

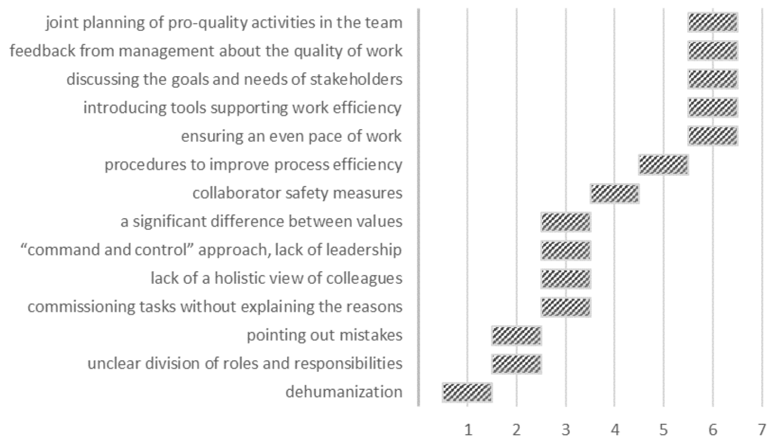
The budget distribution of the surveyed projects was relatively uniform across different ranges, with a slight dominance of projects exceeding €500,000. Most projects had a planned implementation time of 1-2 years, with a statistically significant relationship between budget size and implementation time ($p<0.001$). Among participating organizations, 28% were very large (over 1,000 employees), and 25% were small. Micro-enterprises and large organizations were less represented. The most common industries included IT, non-governmental organizations, cultural organizations, construction, energy, and public administration. Manufacturing companies constituted 40 of the surveyed organizations, with nine being from the automotive industry.

Respondents were inquired about the project methodologies employed in their work, allowing multiple answers due to potential experience across different projects and organizations. Over half of the respondents reported using their methodology. Agile, Scrum, and Kanban methodologies were primarily mentioned in the IT, automotive, and transportation industries. Waterfall methodologies were more prevalent in consumer goods production and industrial sectors. The Project Cycle Management (PCM) methodology was predominantly used in cultural institutions.

An absence of any project management methodology was most frequently reported by educational institutions (71%), consulting institutions (60%), and public administration (54%). The waterfall and agile methodologies were more commonly utilized by respondents working on longer projects with larger budgets. In large and very large organizations, methodologies were applied twice as often as in organizations with fewer than 250 employees.

4.2 Survey results

High quality is achieved thanks to people, their commitment, and innovation. Moreover, the management staff must use suitable approaches and techniques and present the right attitudes. Respondents were asked to indicate how their motivation, commitment, and innovation would be influenced by selected situations (Fig. 2). The situations were presented randomly to avoid filling in the questionnaire mechanically. In their assessments, respondents chose the highest level of answers (definitely positive) less often than in other questions. There were also fewer responses declaring no impact. The median's absolute deviation was low, proving the answers are consistent.



Legend: 1 – definitely negative, 2 – negative, 3 – rather negative, 4 – no impact, 5 – rather positive, 6 – positive, 7 – definitely positive.

Fig. 2. Influence of project manager's behavior on motivation

Only 6% of the respondents declared using the B.W. Tuckman model in accordance with its assumptions. At the same time, however, 75% partially use this model (Fig. 3). Respondents could select several answer options if they were not mutually exclusive. These findings are consistent with previous literature studies. There is a need to reformulate the model of building a project team that will respond to contemporary challenges faced by teams. At the same time, it is worth moving away from teaching and presenting the B.W. Tuckman model in the project management frameworks and handbooks as the current and binding rule.

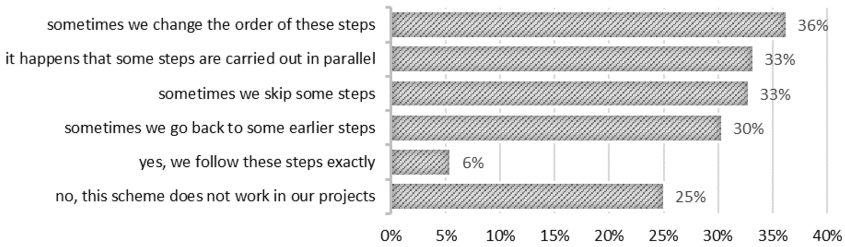
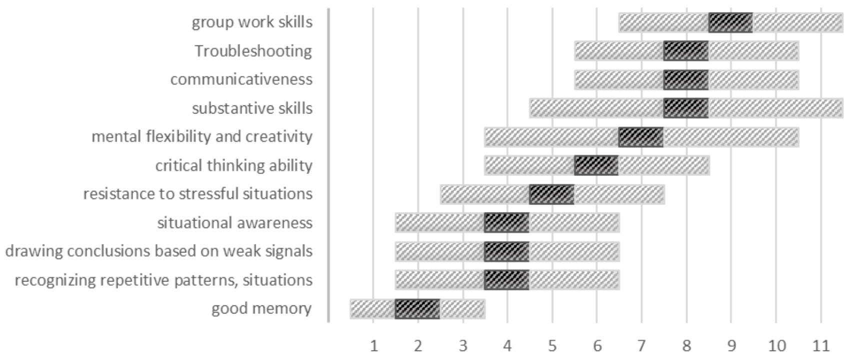


Fig. 3. Application of the B.W. Tuckman model to build a team

According to the assumptions, older respondents use this model slightly more often – the number of indications increases from 2% in the group under 25 to 9% in the groups over 45. There are also industry specifics, and the model is more often used in the construction and automotive industries and less often in public administration, trade, financial services, or cultural institutions.

The study participants were asked to create a ranking of the competencies of project team members and project managers. In the first case, they were given a choice of 11 characteristics of a team member, and in the second, 10 characteristics of a project manager were selected based on the results of a literature review. The optimal way to conduct this study would be a pairwise comparison. However, with so many answer options, it would mean asking dozens of questions. The negative effect of using the ranking technique is the lower consistency of assessments. This effect can be minimized in the future in detailed studies devoted to this topic.

Teamwork was considered the most important competence of a team member, followed by problem-solving and communication skills (Fig. 4). These competencies are used practically regardless of the project's specifics, hence their high position in the ranking. Most doubts arose concerning the importance of substantive skills, flexibility, and creativity. It can be assumed that it is related to the type of results delivered in the project. Substantive skills were more valued in consulting, automotive, and transport and less in non-governmental organizations and companies producing consumer goods.



The median (dark bars) and the absolute deviation of the median (light bars) are marked on the graph.

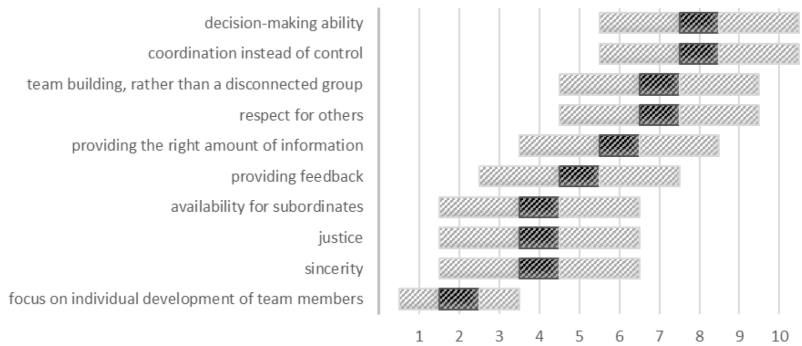
Fig. 4. The importance of competencies of project team members

Many respondents placed critical thinking skills and resistance to stressful situations near the middle of the ranking. These are appreciated competencies, but they are not fundamental. Critical thinking was more valued in educational institutions and the transport industry. At the same time, stress resistance was given more attention by respondents from the construction industry, food production, and non-government organizations (NGOs).

Situational awareness and analytical skills were classified as less important. While these are important competencies, they may be limited to a few team members, and probably not in every project they are fully used. The ability to detect repetitive patterns was valued more in the IT, transportation, and financial services industries and less in NGOs, education, and cultural institutions. In turn, the ability to analyze weak environmental signals was more often pointed out by respondents from the construction, energy, and industrial goods industries. Situational orientation was rated as more important in trading.

The least important competence, with a higher agreement of the respondents, was a good memory. It was slightly more important for design companies and less for education and consulting, which is surprising.

Regarding the project manager competencies, the most important were decision-making skills and “coordination instead of control” (Fig. 5). These two competencies were more often placed at the top of the ranking than the others. Respondents’ understanding of decision-making skills needs further clarification, especially in the context of attaching little importance to leadership. It is not clear whether it is about individual or rather group decision-making. Regarding coordination instead of control, there is an inconsistency with the answers to the previous question on the “command and control” approach. It was assessed as only slightly demotivating, while avoiding this approach is the most important thing here.



The median (dark bars) and the absolute deviation of the median (light bars) are marked on the graph.

Fig. 5. The importance of the project manager’s competencies

Next came team building and showing respect for others. This may reflect the high importance of teamwork skills for project team members.

Even though the factors related to communication were the most motivating, the project manager’s competencies related to ensuring the right amount of information and accessibility were in the middle of the list. They are undoubtedly treated as necessary but not crucial. Representatives of public administration appreciated these competencies more. The fairness and sincerity of the project manager were assessed as slightly less important competencies. Representatives of the transport industry paid more attention to fairness and sincerity.

At the very end, with a lower rating and higher consensus, there was an orientation towards the individual development of team members. Development is an important factor of pro-quality culture. However, it is possible that development issues are transferred to the organizational level due to the relatively short time of project implementation and are not accounted for by project members. Another reason may be the assumption that development is an individual matter for each employee. This would not be the right approach in terms of quality assurance. Interestingly, representatives of educational and advisory institutions rated this competence the lowest. The same industries previously rated the importance of good memory lower.

Comparing the managers' answers with the project team members did not show statistically significant differences in assessing the importance of the discussed competencies in both rankings.

5. Discussion

Effective communication and well-thought-out management processes are critical motivating factors for project team members. Providing employees with clear instructions and expectations fosters engagement and commitment to achieving project goals. Moreover, transparent communication channels nurture trust and collaboration among team members, enabling them to work more efficiently and effectively. These findings confirm previous research on the importance of communication [21], involvement in setting and achieving goals [33], and trust [24].

Involving team members in planning pro-quality activities significantly impacts project outcomes. Active participation in planning and decision-making processes motivates team members and promotes commitment to achieving project objectives. Joint planning also fosters a sense of ownership and responsibility among team members, enhancing quality outcomes, which confirms the results obtained by Gustavsson et al. [33]. Project managers must recognize the importance of active participation and collaboration during the planning phase, ensuring team members' engagement and investment in the project's success. By embracing a collaborative approach, project managers can harness diverse skills and perspectives, ultimately contributing to improved project quality and overall performance.

Understanding and addressing stakeholder requirements are essential to project success [23]. Project team members should actively participate in discussions and decision-making processes related to stakeholder needs. Providing specific, substantive feedback on project deliverables' quality helps identify areas for improvement and reinforces the importance of quality in project outcomes. This encourages team members to strive for excellence and maintain a pro-quality mindset throughout the project.

The survey results suggest that increased use of safeguards against potential liability for errors may indicate a fear-driven work environment where employees prioritize protecting themselves from blame over fostering collaboration and innovation. This phenomenon has already been noticed by Moura et al. [24]. This defensive approach can waste resources and reduce efficiency, as team members may hesitate to take risks or share ideas due to fear of repercussions. To enhance project quality through effective team management, organizations should focus on building trust and promoting a culture of shared responsibility and learning. Encouraging open communication, acknowledging mistakes as opportunities for growth, and emphasizing the importance of teamwork help create a supportive environment where team members feel empowered to contribute fully to their skills and expertise, leading to improved project outcomes and increased stakeholder satisfaction. This is in contradiction with Ngereja and Hussein [37], who showed a positive relationship between performance assessments and team innovation. In the tradition of pro-quality approaches, e.g., in Deming principles, it is assumed that trust and openness should replace assessments.

Situations that motivate project team members, as presented in Fig. 2, suggest that respondents considered joint planning of pro-quality activities, stakeholder requirements, and specific feedback on achieved quality as most important. Efficient methods and procedures also contribute to motivation. Good communication and well-thought-out management processes are key motivating factors. The top demotivating factors are pointing out mistakes rather than discussing solutions, unclear division of roles and responsibilities, and dehumanizing co-workers. Proper task planning and division of responsibilities are crucial to avoid these issues. Investing more time in project planning can eliminate the above-mentioned factors, especially in longer projects. Discussing solutions, rather than errors, can improve motivation and future results. This confirms studies that highlight the role of transparency [33], openness, cooperation [20], and attitude [21].

Focusing on team members’ mistakes without offering constructive solutions can have a detrimental impact on motivation levels. Such an approach can create a hostile working atmosphere and hinder the team’s ability to learn from their mistakes. Instead, project managers should encourage open communication and problem-solving, allowing the team to address issues collectively and foster a more supportive environment. Psychological safety leads to a better exchange of ideas and creates a pro-quality culture [29].

Addressing ambiguity in roles and responsibilities is essential for team performance and project quality. The lack of clear definitions and expectations can lead to inefficiencies and frustration among team members, ultimately affecting the project’s overall success [23]. Conversely, when roles and responsibilities are clearly defined, team members experience a greater sense of ownership and accountability, contributing to improved motivation and engagement. This highlights the crucial role of project managers in ensuring that expectations and responsibilities are well-communicated and understood by all team members. In doing so, project managers can foster a more cohesive and effective team, ultimately enhancing the quality and outcomes of their projects.

The findings suggest that treating team members as tools or machines negatively impacts motivation and collaboration. This dehumanization hinders team dynamics and stifles creativity and innovation, ultimately affecting overall project quality. Promoting a human-centered approach to management fosters a more supportive and engaging work environment. As found by Hefley and Bottion [17], it is especially important for young project managers who underestimate soft skills. Recognizing team members’ individual needs and contributions encourages personal and professional growth. This approach builds trust and commitment within the team and drives members to strive for excellence in their work, ultimately leading to enhanced project quality. Adopting a human-centered management style enables project managers to better understand team members’ unique strengths and weaknesses, facilitating more effective allocation of resources and tasks and ultimately contributing to project success.

Insufficient planning can result in unclear roles and responsibilities, leading to confusion and frustration within the project team [17]. This can ultimately affect team motivation and project quality. To avoid these consequences, project managers should allocate sufficient time during the project initiation phase to develop comprehensive plans, ensuring that tasks and responsibilities are well-defined and understood by all team members.

Project managers play a crucial role in defining and communicating the roles and responsibilities of team members. By setting clear expectations and providing guidance, project managers can help create a sense of ownership and accountability among team members. This improves team motivation and contributes to the overall quality of the project outcomes.

The study implies that small enterprises may embrace ambiguous roles and responsibilities due to employees assuming multiple roles, fostering innovation, and positively impacting project quality. Conversely, large enterprises may struggle to define roles and responsibilities due to a larger workforce and complex project structures, potentially lowering project quality. Therefore, tailored team management strategies should be developed to address the specific needs and challenges of different enterprise sizes, ultimately enhancing project quality. This confirms that team competencies should be adjusted to the type and conditions of the project [34].

The findings from this study highlight the importance of effective team management in enhancing project quality. Project managers should focus on fostering open communication, promoting a pro-quality culture, and ensuring clear roles and responsibilities within the team. By doing so, they can create an environment where team members are motivated and committed to delivering high-quality results.

Based on the insights gained from this study, project managers, team leaders, and organizations should consider the following recommendations to improve project quality through effective team management:

- Invest time in developing comprehensive project plans that clearly define tasks and responsibilities. Identification of multiple ways of implementing a project, as well as potential problems associated with them, increases the project manager’s situational awareness, reduces the technical debt, and facilitates making good decisions during the project.

- Encourage open communication and collaboration among team members. Collaboration and exchange of ideas contribute to early detection of problems, increased innovation, and team involvement. At the same time, excess communication, e.g., keeping everyone informed about everything, can limit efficiency.
- Focus on identifying and addressing stakeholder requirements. Incorrect or incomplete identification of stakeholder requirements may result in project results passing the verification stage, which is based on documented requirements, but being rejected at the validation stage, which is based on the real requirements.
- Provide specific, substantive feedback on project deliverables to reinforce the importance of quality. Acceptance of low-quality results by stakeholders and the project manager leads to demoralization of the team members and a gradual reduction in their quality orientation.
- Promote a supportive working environment by discussing solutions rather than highlighting mistakes. Dehumanization and emphasizing mistakes are indicated by respondents as the factors that limit motivation to the greatest extent.

By implementing these recommendations, organizations can better leverage the power of effective team management to enhance project quality and achieve desired outcomes.

6. Conclusions

The research findings emphasized the importance of effective team management in enhancing project quality. Critical factors such as communication, comprehensive planning, clear roles and responsibilities, stakeholder requirements, and a supportive work environment were identified as essential elements contributing to project success.

This study makes a theoretical contribution to the field of project quality management by examining the interplay between team management and project quality. Through an analysis of empirical data collected from diverse industries and projects, this study sheds light on the key factors contributing to project success. These factors include effective communication, thorough planning processes, well-defined roles and responsibilities, alignment with stakeholder requirements, and cultivating a supportive work environment. The findings unequivocally underscore the paramount importance of adopting appropriate management approaches, employing proven techniques, and fostering the right attitudes to achieve high-quality project outcomes. Additionally, this study advocates for a human-centric management approach, emphasizing the requisite focus on employee involvement, commitment, and innovation to enhance project quality and ultimately attain desired objectives.

For practice, the study presents evidence-based recommendations to enhance project quality through effective team management. The study suggests that investing time in developing comprehensive project plans is crucial. This involves outlining project objectives, outlining the tasks and responsibilities of team members, and conducting a thorough assessment of potential challenges and risks. This approach enables project managers to enhance their situational awareness, minimize technical debt, and make informed decisions throughout the project lifecycle.

Furthermore, the study emphasizes fostering open communication and collaboration among team members. This can be achieved by establishing clear communication channels and facilitating regular meetings and discussions. Effective communication promotes early detection of problems, increases innovation, and encourages team involvement. It is important, however, to strike a balance between collaboration and excessive communication, as excessive communication can impede efficiency and productivity. Therefore, project managers should implement effective communication strategies that keep team members informed without overwhelming them with unnecessary details.

Additionally, the study emphasizes the significance of identifying and addressing stakeholder requirements. Proper identification and understanding of stakeholder needs are crucial to project success. This necessitates the active participation of team members in discussions and decision-making processes related to stakeholder needs. By providing specific, substantive feedback on project deliverables, project managers can reinforce the importance of quality and facilitate continuous improvement. This feedback loop ensures project outcomes meet stakeholder expectations and prevent potential issues from escalating.

To promote a supportive working environment, the study recommends that project managers prioritize discussing solutions rather than highlighting mistakes. This approach avoids demoralizing team members and fosters a culture of learning and improvement. By acknowledging mistakes as opportunities for growth, project managers can create a psychologically safe environment where team members feel comfortable sharing ideas and thoughts. This, in turn, stimulates creativity, innovation, and collaboration, ultimately leading to enhanced project quality.

While having a large sample size, this study may contain possible biases in the sample population and may not fully represent all industries and project teams. The study's cross-sectional nature also limits its ability to capture the dynamics of team management over time. Future research could benefit from incorporating interviews or deepened case studies to provide more insightful conclusions.

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Appendix A. Questionnaire

1. How would the following situations affect your motivation, commitment and innovativeness in the project (scale: 1 – strongly disagree, 2 – disagree, 3 – slightly disagree, 4 – neutral, 5 – slightly agree, 6 – agree, 7 – strongly agree; random order of answers)?
    - significant difference between me and organizational values
    - dehumanization – team members treating me as another tool, computer, machine
    - pointing out the mistakes made instead of discussing possible solutions to the problem
    - creating measures by team members against potential liability for errors (redundant correspondence, unnecessary papers)
    - focusing by team members only on their tasks, lack of a holistic view, limiting to performing only assigned tasks
    - unclear division of roles and responsibilities, imprecise expectations of the managers
    - giving tasks without explaining the reasons or connection with the client’s requirements
    - “command and control” approach – no leadership, relationships limited to performing and controlling the tasks
    - all team members planning together the activities leading to improving the quality
    - communicating and discussing the goals, needs, and expectations of stakeholders
    - introducing procedures and policies to increase the efficiency of processes
    - introducing tools supporting work efficiency
    - ensuring an equal pace of work, without overtime and waiting for others
    - frequent, specific, and substantive feedback from management about the quality of my work

2. B.W. Tuckman formulated the steps for creating a project team, including forming, storming, norming, and performing. Do these steps work for the projects in which you participate? Please choose all that apply (yes/no):
    - yes, we follow these steps exactly one after the other in the same order
    - it happens that we go back to some of the previous steps (e.g., in the case of the new team member)
    - it happens that some steps are carried out in parallel (e.g. by different sub-teams)
    - it happens that we change the order of these steps depending on the needs of the project
    - it happens that having experienced team members, we skip some steps
    - no, this scheme does not work for our projects
    - other

3. Please rank the competencies of the project team members in order of importance, starting with the most important ones (ranking).
    - situational awareness
    - good memory
    - drawing conclusions from weak signals in the project environment
    - the ability to recognize repeating patterns, situations
    - effective troubleshooting
    - mental flexibility and creativity
    - ability to work in a group
    - communicativeness
    - expert skills important for the project
    - resistance to stressful situations
    - critical thinking skills

4. Please prioritize the project manager’s competencies in order of importance, starting with the most important ones. (ranking)
    - coordinating instead of controlling
    - availability for team members
    - giving the right amount of information
    - providing feedback

- justice
- ability to make decisions
- sincerity
- focus on individual development of team members
- building a team instead of an unrelated group of people
- respect for others

5. Sex
   - Female
   - Male
   - Other
   - I refuse to answer

6. Age (in years)
   - below 18
   - 18 - 25
   - 26 - 35
   - 36 - 45
   - 46 - 55
   - 56 - 65
   - 66 or above
   - I refuse to answer

7. Total experience (years)

8. Experience in projects (years)

9. The function performed in the current project (or the last completed one), e.g. project manager, analyst, team member

10. Education
    - basic
    - junior high school
    - vocational
    - secondary
    - higher
    - PhD or more

11. Education profile. You can give a few, starting with the most important, e.g., technical, managerial, economical, chemical

12. Number of employees of the organization in which you work.
    - less than 10
    - 10 - 49
    - 50 - 250
    - 250 - 1000
    - more than 1000

13. Please provide the type of organization and the main branch/industry in which it operates, e.g., a chemical industry company, local government office, university

14. The size of the town where the branch of the organization where you work is located.
    - village
    - city up to 50,000 residents
    - city 50,001 – 150,000 residents
    - city 150,001 – 500,000 residents

- city with over 500,000 residents
- I work only remotely (100% of my working time)

15. Please provide the size of the project team
    - less than 5
    - 5 - 10
    - 11 - 20
    - 21 - 30
    - more than 30

16. Please provide the size of the project budget
    - less than €10 000
    - €10 000 - 20 000
    - €20 001 - 100 000
    - €100 001 - 500 000
    - more than €500 000

17. Please provide the planned period of the project.
    - less than 6 months
    - 6 - 12 months (up to 1 year)
    - 13 - 24 months (up to 2 years)
    - 25 - 60 months (up to 5 years)
    - more than 60 months

Biographical notes

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A comparison of soft factors in the implementation and adoption of digitalization projects: a systematic literature review

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Abstract:
This study expounds existing literature on digitalization projects taking a one-dimensional view on people at organizational, project and individual levels. Through a systematic literature review, we highlight and contrast the impact of soft factors on the implementation and adoption of digitalization projects. Four core enablers were identified and contrasted at different organizational levels in an integrated framework for successful implementation and adoption of digitalization projects. Findings indicate that both adoption and implementation of digitalization projects have similar core enablers at organizational level, significantly different actions that need to be taken at project level and slightly different characteristics at individual level. Moreover, eight critical soft factors were identified for successful implementation and adoption of digitalization projects. The findings provide valuable insights to practitioners and enable controlling the highest value factors to increase the success rate of digitalization projects and to identify the core elements that need attention at various organizational levels. To the best of our knowledge, this is the first systematic literature review that expounds the extent of knowledge available on success factors within the context of digitalization projects taking the single dimensional focus on people at different organizational levels.

Keywords:
digitalization project; digital transformation; individual success factors; literature review.

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1. Introduction

Nearly 70% of the organizations studied by the Project Management Institute indicated their involvement in digital transformation (DT) initiatives in 2020 [1]. The number suggests a growing trend to initiate digitalization projects in the current business environment [2], facilitated by technology advancement [3]. Subsequently, researchers have made significant efforts to define digitalization projects. Sanchez-Segura et al. [4] define such projects as those developed in the DT process; Henriette et al. [5] define them as those involving the implementation of digital capabilities to support business model transformations whereas Grahn et al. [6] define them as projects involving introductions of digital tools. Although there is no an universal definition, there is consensus that digitalization projects involve the introduction or use of digital tools [6-8] and are undertaken to spearhead DT in organizations [4, 5, 9]. We define a digitalization project as one that introduces a digital tool that is implemented as part of the organization's DT.

Digitalization has attracted researchers' attention leading to research development on the topic. Such research include, for instance, barriers [10, 11], success factors [12, 13], impact and benefits [14], complexity [15], competences [16], soft skills [17, 18] and soft factors [19-21]. Existing research has focused on several dimensions of DT (i.e., people, technology, and processes), leading to generalization of factors making it challenging to understand and address explicitly the factors in the people dimension.

For successful digitalization projects, the people dimension needs attention [22]. Both technical and soft capabilities are required [23-26], but because soft factors are "hidden", likewise are easily neglected [27]. Hence, there is a need to create a deeper understanding of the influence of people dimension in the success of digitalization projects. We acknowledge the influence played by the "technology" and "process" dimensions on overall DT outcomes, but this study explicitly focuses on the "people" dimension by illuminating the significance of various soft factors for the success of digitalization projects.

The success rate of digitalization initiatives in 2012-2018 was between 16–20% [4], which is very low. Although researchers have attempted to expand the knowledge on digitalization projects, the topic has yet to gain attention within project management (PM) research. This is evident from the low number of scientific papers published in PM journals exclusively focusing on digitalization projects. In January 2023, we performed a search in Scopus for the terms "digital transformation project" and "digitalization project"/"digitalisation project" which resulted in a maximum of three hits for nine PM journals listed on Scimago Journal & Country Rank (SJR). The term "digital transformation" dominated returning 96 hits for all nine journals together, each of which had at least one hit. These journals are; (i) the Baltic Journal of Management, (ii) Procedia Computer Science, (iii) Journal of Modern Project Management, (iv) International Journal of Project Organisation and Management, (v) International Journal of Information Systems and Project Management, (vi) Built Environment Project and Asset Management, (vii) Project Management Journal, (viii) International Journal of Project Management and (ix) International Journal of Managing Projects in Business. On the contrary, the topic is discussed vastly in several conferences. A search conducted at the same period and database for conferences resulted in 5,907 hits for the term "digital transformation," 76 for "digital transformation project," and 75 for "digitalization projects," indicating an overall increase in interest in different research areas.

Digitalization projects are new, complex, and increasingly numerous and specific [28], hence making them different from traditional information technology (IT) projects [29-32]. Digital era has led to development of new organizations, systems, processes, leadership, ways of managing, and social aspirations requiring digitalization projects its own PM method [28]. Digitalization projects redefine a company's value proposition, aim to change an organization's identity, and drive a new business strategy, which differs from a traditional IT project that aims to support and enable the existing strategy and identity [32]. Project managers managing digitalization projects need proper means to unite the key factors of success of digitalization projects: flexibility, speed, creativity, transversely, globalist and business skills [28]. This study is an attempt to contribute to research dedicated on digitalization projects.

Successful outcomes of digitalization require focusing on adoption as much as implementation [33]. Nevertheless, existing studies have contributed to the topic through focusing on either adoption [10, 34, 35], implementation [12, 21, 36], or both [37, 38]. Furthermore, the factors affecting adoption of technological innovations and those affecting implementation have been found to be entirely different [38]. During adoption it becomes more critical to ensure that the organization's culture and ways of working are in support of the overall DT [29]. There is a need to develop more insights on what exactly are similar and what are different in implementation and adoption, which this study aims to address. We refer to implementation as the undertaking of the project by the organization (i.e., translating the digital strategy into plans and actions). We use the word "implementation" in a broad and comprehensive manner to cover a set of capabilities, resources, and actions [31]. By contrast, we refer to adoption as the integration of digital technologies into the day-to-day operations by the end users.

This paper is organized as follows. The next section presents the theoretical background. The third section discusses the review process including the screening and appraising the relevant papers. The fourth section presents the results from the frequency and content analyses. The fifth section discusses the results through an integrated framework. The last section presents the conclusion where the contributions, suggestions for future studies and limitations of the study are highlighted.

2. Background

2.1 Project success factors

Project success factors constitute a set of circumstances, facts, or influences that contribute to the project outcomes (i.e., success or failure of a project), but the factors do not form the basis of the judgement [39]. Project success research has evolved over the years. Jugdev and Müller [40] classify the evolution of the understanding of project success into four periods. Period 1 between 1960s-1980s included the use of simple metrics to rate project success, minimal customer involvement and emphasized hard skills than soft skills. Period 2 between 1980s-1990s emphasized the development of critical success factor (CSF) lists and focusing on stakeholder satisfaction as an indicator of success. Period 3 between 1990s-2000s is when integrated frameworks for project success emerged. Period 4 which is the 21st century, included benefits to the organization and preparation for the future as a success dimension.

Since the development of CSF lists in the 1980s [40], several CSF lists have been created in varying contexts, for example, for Information and Communications Technology (ICT) projects [41, 42], petroleum projects [43], and for the influence of several CSFs on project success [44]. Hence, there is no only one list of factors that influence project success [45]. Vast research on project success factors exist but are usually listed in very general terms [46]. Success factors can be either technical or people-related, in most cases, the factors have been found to be people-related [47-49] - also referred to as soft factors. We use, the terms people-related factors and soft factors interchangeably.

2.2 Soft factors facilitating the success of digitalization projects

Strong leadership is crucial in the success of digitalization projects [23, 44, 45] because ongoing changes make it difficult to understand where change is coming from and whether it is unfolding within or across organizational boundaries [50]. Digital leaders require soft skills such as negotiation, influence, and change management [46]. Also, the ability to motivate, drive change, take risks, inspire, and to drive a shared ambition [51]. Nevertheless, both managers and employees at all levels should update their skills in order to tackle digitalization challenges [52].

Furthermore, the support and commitment of top management is crucial in facilitating successful digitalization projects [12, 23]. Top management sets strategies and engages employees [53], allocates resources, addresses employees' concerns, and communicates the project vision. Other soft factors identified as facilitating the success of digitalization projects include the provision of rewards and incentives [27, 54], employees' acceptance of new changes [55, 56], a dedicated and committed team [18, 57], trust and cooperation [27], collaboration [58], employee and manager and learning [59].

Some studies have investigated the relationship between various soft factors in facilitating digitalization projects' success. Hsieh et al. [60] investigate the importance of understanding cultural differences when communicating and collaborating. Larjovuori et al. [23] discuss the role of leadership and employees' well-being in organizations' digitalization processes. Ngereja et al. [20] show the interrelations between various soft factors. Existing literature investigates either the role of specific soft factors or the relationship between several soft factors in the context of digitalization projects, such as the role of a digital leader [61], leadership and employee well-being [23], and culture [55], on digitalization projects' outcome. However, none provides an overview of the significance of soft factors in digitalization projects, and therefore this study will address this. We focus on the "people-view" because people drive DT [62, 63], hence a deeper understanding of the factors that influence people and vice versa will provide meaningful contribution. Thus, this review addresses two objectives:

1. To explore and contrast the impact of soft factors on the success of digitalization projects;
2. To identify the most critical soft factors in digitalization projects.

3. Methodology

This review follows the guidelines for conducting a systematic review by Tranfield et al. [64] and Levy and Ellis [65].

Two main search terms were included in the literature search: "soft factors" and "digitalization projects." A main string was created with four alternative search strings by interchanging the main search terms and searching in three databases which are Web of science, ScienceDirect and Scopus. As there were very few hits from the higher-ranking PM journals, the search was widened to include other journals specializing in business, management, and organization. Only peer-reviewed journals were included as they tend to have high impacts in the field and follow a rigorous review process to ensure quality. Conferences were excluded because although they may be peer-reviewed, they do not have metrics like journals, such as impact factor (IF). Inclusion criteria were applied followed by a thorough screening process. First, only titles and abstracts were screened for relevance then a second screening was done by scanning through the whole paper to check if the topic was related to success within the context of DT. The papers that were classified as relevant at the second screening were downloaded and read through thoroughly which resulted in 39 papers that were addressing the research objectives. The review process is shown in table. 1.

Table 1. The review process

Search strings	(Soft factors OR human factors OR people factors) AND (digitalization projects OR digitization OR digital transformation) ("digitalization project success") OR ("digitization project success") OR ("digital transformation success") ("IT project success") OR ("IS project success") OR ("information systems project success") OR ("information technology project success") (("Soft factors") AND ("digitalization projects")) OR (("soft factors") AND ("digitization projects")) OR (("soft factors") AND ("digital transformation")) (("soft factors") AND ("IT projects")) OR (("soft factors") AND ("Information systems projects")) OR (("soft factor") AND ("IS projects)) OR (("soft factors") AND ("information technology")) ***Search strings were repeated with "human factor" and "people factor" instead of "soft factor" and modified according to the database*		
Databases	Web of Science	ScienceDirect	Scopus
Inclusion criteria applied	1. Language: English 2. Document type: journals 3. Content type: must be conducted in the context of digitalization projects or be relevant in the context of digital transformation and include content on success factors of a soft nature (i.e., human/people-related factors)	Does the paper match the set criteria?	Papers included: Web of Science (n =153) Scopus (n =366) ScienceDirect (n =384) **Total = 903 papers**

First screening	Endnote files were downloaded and imported into the referencing software EndNote. • Duplicate records removed (n =3) • Conferences, books, book chapters, posters, reports, and predatory journals (n =278) • The titles and abstracts of the remaining publications were screened and excluded if they lacked the following criteria: - No mention of digitalization projects, digital transformation, or success factors (n=375) - Papers included in the next step of the review (full paper reading) = **247 papers**
Second screening	The papers were downloaded, and a second screening was done where further exclusion was done if there was: • No relevance to success of digitalization projects, digital transformation projects or digital transformation (n=162) - Papers included in the next step of the review (full paper reading for data extraction) = **85 papers**
Full paper reading	Green, red, and yellow color coding was used to classify the papers based on their relevance to address the research objectives. Green = very relevant (n=39); Yellow = relevance unclear (n=36); Red =irrelevant (n=10) - Papers included in the next step (Green) = **39 papers**
Quality assessment	Journal quality criteria (must meet any two criteria) 1. ABDC ≥ B 2. IF ≥1 3. SJR ≥ Q2 4. Harzing's Journal Quality List ≥ B Is the journal of high quality? 4 papers excluded from final analysis; papers included in the analysis (co-occurrence, frequency, and content analyses) = **35 papers**

Four journal ranking frameworks were applied: (1) journal IF, (2) SJR score, (3) Harzing's Journal Quality List (JOURQUAL), and (4) ABDC Journal Quality List. These established frameworks provide indicators of the quality and status of journals. We included journals with IF ≥ 1 reported in 2021. The Scimago Journal & Country Rank (SJR) score ranks journals from Q1 to Q4, where Q1 represents the top 25% journals and Q4 represents the 25% lowest ranked journals. Using the SJR 2021 score, we included Q1 and Q2 journals. The JOURQUAL includes five ranks ranging from A+ to D. We included journals ranked A+, A, B, and C, indicating *"world leading*," *"leading*," "*important and respected*," and *"recognized"* respectively. The ABDC ranks journals in four categories, A*, A, B, and C, indicating *"leading," "highly regarded," "well regarded,"* and *"recognized."* We included journals ranked A*, A, or B in 2019. Only journals listed in at least two of the four ranking frameworks were included, reducing the total number of papers to 35.

4. Data synthesis and findings

4.1 Data trends in selected paper

The selected papers were published between 2005–2021. A steady increase in publications was observed in the period 2016–2021, with majority of the papers (81%) published in that period suggesting a recent recognition of research on soft factors within the context of digitalization projects. Qualitative methods dominated (66%), followed by quantitative methods (28%), and a mix of both methods (6%). Interviews appeared to be the dominant method of data collection (40%), followed by questionnaires (31%), secondary methods (e.g., reviews, secondary sources, observations, meetings, workshops) (26%), and mixed approach method (3%). Inclusion of perspectives cross-cutting organizational levels enables to gaining of deeper insights [66]. Selected studies had respondents from top management positions (28%), management-level positions i.e., senior, and junior project managers (31%), employees/team members (17%) and members of the organization regardless of position (22%) and undisclosed (2%). The study participants in selected papers included international respondents dispersed across countries and continents. Of all papers, 31.2% had unspecified location while 20.3% comprised participants from a mix of countries. Those with specified location (48.5%), the majority report studies were conducted in Europe (28.6%), Asia (11.4%), US (5.7%) and Canada (2.8%).

Several digital technologies are discussed in the selected papers; Internet of Things (IoT) (31.4%), big data (14.3%), cloud computing (11.4%), artificial intelligence (AI) (8.6%) and automation (2.9%). However, majority of papers (31.4%) only discuss digitalization projects in general.

4.2 Addressing study objectives

Objective 1: For data extraction and analysis, VOSViewer software and content analysis were applied. VOSViewer was used to check author keyword co-occurrence. The keywords with the greatest total link strength with other keywords were identified, followed by content analysis. Since digitalization projects are conducted as part of the overall DT, this review focuses on both implementation and adoption to gain a holistic understanding of both. Three clusters were observed relevant to our study: (1) challenges, (2) barriers, and (3) success factors of digitalization project implementation and adoption. Each of the papers discusses either one or more of these aspects.

Clusters 1&2: Challenges and barriers (inhibitors)

34% of papers discuss challenges and 26% discuss barriers. Clusters 1 and 2 were merged, since they both presented factors that inhibit (i.e., barriers and challenges) digitalization project success. From Table 1, both implementation and adoption share challenges rooted in organizational culture, communication, and learning, but differ regarding the ‘know-how’ and ‘why’. Implementation challenges are related to bureaucracy and lack of preparedness while adoption challenges are related to lacking a unified goal and inability to rethink and restructure new work.

Cluster 3: Success factors

Cluster 3 contains papers that discuss people-related success factors of digitalization projects implementation and adoption (79%). From Table 2, the success of digitalization projects is rooted in four main factors: (1) leadership, (2) culture, (3) capabilities development, and (4) top management support. During implementation, the digitalization leader is needed to push agendas that focus on achieving buy-in, while in adoption the focus is sustaining the buy-in. In building a like-minded culture, the focus in implementation is on individual mindsets, while in adoption the focus is on creating a collective mindset. For top management commitment, the focus in implementation is on managing bureaucracy and organizational politics, as this is where most challenges arise, while in adoption the focus is on investing in human resources to ensure that people have the tools needed to continuously integrate new changes. In developing capabilities, the focus in implementation is on knowledge exploration, while in adoption the focus is establishing proper mechanisms that support knowledge exploitation.

Table 2. Inhibitors and success factors of digitalization projects

<table>
<tr><th></th><th>Inhibitors of digitalization projects</th><th>References</th><th>Success factors of digitalization projects</th><th>References</th></tr>
<tr><td rowspan="2">Project implementation</td><td>Bureaucracy and organizational politics:
• Inability to react on a timely manner.
• Lack of a sense of urgency.
• Remain reluctant to adapt to changing nature of business.</td><td>[67]; [68]; [69]</td><td>A highly skilled leader:
• Setting a clear vision.
• Identifying and engaging with relevant stakeholders ‘end-user involvement’.
• Effective communication throughout the organization.
• Building strong collaboration strategies.
• Willingness to take risks in an uncertain environment.
• Resistance management.</td><td>[70]; [71]; [72]; [73]; [74]</td></tr>
<tr><td>Development of human resources:
• Identification of new skills and training requirements.
• Management of the changes in employee positions, tasks, and responsibilities.
• Difficulty in retaining young employees.
• Identification of required expertise.</td><td>[75]; [68]; [76]; [69]; [77]; [78]</td><td>Top management support and commitment:
• Rewarding digital initiatives.
• Provision of resources.
• Investment in human resource development strategies.</td><td>[79]; [68]; [21]</td></tr>
</table>

	Inhibitors of digitalization projects	**References**	**Success factors of digitalization projects**	**References**
	Lack of preparedness to tackle digitalization: • Low level of understanding of what digitalization entails. • Unclear or lack of vision. • Inability to define complex processes early. • Unclear definition of roles and how they will change. • Inability to clearly define the "why".	[70]; [67]; [76]; [69]; [77]	*A like-minded culture:* • A culture in which people support each other. • A culture supportive of change. • Having self-motivation and a sense of ownership. • Taking the initiative to learn. • Building trust between leaders, managers, and employees.	[72]; [73]; [59]; [80]
	Having a rigid culture: • Units working independently in silos. • Weak internal and external collaborations. • Failing to prepare people for the change. • Technology oriented culture. • Lack of initiatives/taking charge. • A culture of complacency (no sense of urgency). • Lack of a flexible and adaptable mindset.	[70]; [67]; [77]; [72]; [59]	*Building employee capabilities:* • Provision of training for both social and technical expertise. • Giving room for experimentation. • Managing the learning process.	[71]; [81]; [74]; [21]
	Lack of proper knowledge-sharing mechanisms: • Training without defining the knowledge gap. • Knowledge not readily and widely available. • Lack of mechanisms to utilize acquired knowledge. • Improper knowledge-sharing mechanisms 'people do not know what others know'.	[4]		
	Communication-related issues: • Increase in heterogenous ways to communicate (increases complexity and frustration). • Decreased sense/perception of information security. • Inability to clearly communicate new regulations.	[59]		
Project adoption	*Lack of a unified communication protocol:* • Lack of clarity on how to integrate and share information. • Dispersed information posing safety and security concerns. • Increase in heterogenous ways of communicating (increases complexity and frustration). • Decreased sense/perception of information security. • Inability to communicate new regulations clearly.	[10]; [11]; [34]	*Skilled leader to lead the transformation:* • End user involvement. • Effective communication of the new circumstances. • Building a culture with strong connectedness of employees.	[74]; [82]
	Development of human resources/capabilities: • The need for continuous learning. • Lack of appropriate expertise. • Shortage of skills and a qualified workforce.	[83]; [10]; [11]	*Top management support and commitment:* • Rewarding digital initiatives. • Provision of resources • Investing in human resource development strategies.	[82]; [68]; [79]
	Unable to build a change culture: • Lack of a common mindset • Unable to build a strong collaborative culture	[10]; [11]	*A supportive environment/culture:* • Organization has the capacity to change. • Presence of collaborative culture. • Environment that supports new ways of working.	[79]; [72]

	Inhibitors of digitalization projects	References	Success factors of digitalization projects	References
	Unclear vision of transformation: • Having contradicting interests between units. • Not having a clear and unified goal throughout the organization (i.e., each unit has a different goal). • Facing resistance from people in the organization.	[11]; [71]	*Building employee capabilities:* • Access to skilled/ experienced employees. • Managing the learning process. • Having knowledge seeking employees.	[82]; [68]; [81]
	Unable to rethink and restructure new work, including: • Conflict management. • Leading in the new digital context. • Shaping the culture in the digital context. • Inability to evaluate, prepare, and accept new. requirements, regulations, and standards.	[59]; [75]		

Objective 2: Frequency analysis was conducted to address this objective as it enables identification of number of occurrence of a factor thus indicates emphasis and the recognition among researchers. To rank the factors, a normalized value method was calculated for each factor using the formula;

Normalized value (NV)= (mean – minimum mean) / (maximum mean – minimum mean).

Soft factors identified from the review are listed in Table 3, from highest to lowest frequency of occurrence. Eight critical soft factors with ($n \geq 5$) were identified as having gained most recognition among researchers. These are learning, organizational support, collaboration, organizational leadership, end user involvement, organizational culture, provision of training, and soft skills of project manager.

Table 3. Soft factors identified as important for successful digitalization projects.

Soft factors	Reference	frequency	normalized value
Learning	[29]; [84]; [85]; [19]; [12]; [86]; [81]; [59]; [21]	9	1.000
Organizational support	[70]; [79]; [29]; [67]; [12]; [68]; [87]; [54]	8	0.875
Collaboration	[85]; [73]; [80]; [56]; [81]; [59]; [58]; [82]	8	0.875
Organizational culture	[84]; [19]; [68]; [73]; [56] [58]	6	0.625
End-user involvement	[70]; [79]; [29]; [71]; [21]	5	0.500
Organizational leadership	[68]; [54]; [56]; [81]; [82]	5	0.500
Provision of trainings	[71]; [19]; [68]; [54]; [74]	5	0.500
Soft skills of project manager	[71]; [19]; [18]; [80]; [81]	5	0.500
Sense of ownership	[56]; [82]; [21]	3	0.250
Communication	[71]; [19]; [54];	3	0.250
Soft skills of team members	[71]; [54]; [80]	3	0.250
Innovation-based mindset	[80]; [56]; [21]	3	0.250
Rewards and recognition	[84]; [54]; [81]	3	0.250
Human resource management	[85]; [68]	2	0.125
Dedicated team	[71]; [85]	2	0.125
Motivation	[80]; [56]	2	0.150
Supportive environment	[79]	1	0

5. Discussion

Our findings show that both implementation and adoption of digitalization projects require multilevel readiness, at organizational, project, and individual level. Patanakul and Shenhar [88] acknowledge the importance of aligning project implementation with higher level organizational strategies and involving people from all organizational levels to execute their roles to achieve the intended business results.

Four core enablers were identified at the organizational level, which we term as organizational leadership, organizational culture, organizational support, and organizational learning, and we consider these as core elements in the governance of digitalization projects. No differences were observed between the core enablers during implementation and adoption at organizational level, therefore, they form the four core enablers in the integrated framework. However, there were significant differences between the actions taken during implementation and adoption at project level. Moreover, the characteristics that team members should possess during implementation and adoption at individual level are relatively similar and in both cases the crucial characteristic is that individuals have the willingness to be a part of the change. These similarities and contrasts are presented and elaborated in the integrated framework (Table 4) below.

Table 4. An integrated framework for the successful implementation and adoption of digitalization projects

Successful implementation				Successful adoption
Individual characteristics of team members	**Specific actions taken at project level**	**Core enablers at organizational level**	**Specific actions taken at project level**	**Individual characteristics of team members**
•Open to new ways of working (e.g., collaborating with external parties)	•Identifying and engaging with relevant stakeholders •Ensuring adequate project governance	**Organizational leadership**	•Ensuring effective end user involvement •Establishing proper communication channels (i.e., digital, and traditional)	•Being open to flexible working conditions (e.g., hybrid working and integrating several communication channels)
•Willingness to take risks in an uncertain and dynamic environment	•Creating a trustworthy project environment	**Organizational culture**	•Identifying and addressing emanating concerns from team members	•Willingness to share own opinions
•Personal motivation for personal development/growth •Open to new roles and tasks	•Affording team members accessibility to different projects and different teams •Allocating suitable mentors to team members	**Organizational support**	• Ensuring manager accessibility for meetings with team members • Evaluating performance to identify areas for improvement	• Having proactive individuals who seek feedback, clarification, and evaluation regarding their performance
•Having a knowledge-seeking attitude •Willingness to take the initiative to experiment with new ideas	•Allowing room for experimentation •Providing training as and when needed	**Organizational learning**	• Establishing proper knowledge sharing mechanisms • Frequent sharing of new requirements, regulations, and standards	•Willingness to share with and learn from others

During implementation, the focus at project level is on stakeholder management and creating opportunities for external collaborations. As digitalization projects are especially focused on experimentation and adaptation [74], engaging with third parties is a commonly used strategy to increase the organizational pool of information and expertise [29]. By contrast, during implementation, the focus is on gaining end users' acceptance and ensuring communication channels are properly integrated into daily tasks.

The focus at the organizational level is on building a like-minded culture. Additionally, the contrast between the actions to be taken at project level is significant for organizational culture. During implementation, building trust is important to facilitate risk-taking by creating a safe environment. During project adoption, the focus is on addressing team members' concerns, such as how the change might affect their work, and the new opportunities or threats that might arise from the change.

At the organizational level, a strong organizational support is crucial. However, at project level, this support appears differently during implementation and adoption. In implementation, the focus is on exposing project team members to several project opportunities so that they can identify where they can contribute best. At individual level, it is important that the team members are open to new tasks and are personally motivated to develop their knowledge. By contrast, during adoption, support is provided through the project manager's accessibility to the team members, which in turn requires team members' proactiveness to seek feedback and clarification.

For implementation of organizational learning, the focus on project level is mainly on experimentation for new knowledge creation. Project managers should support experimentation and identify relevant training sessions for their team members. At individual level, team members should be proactive in sharing their training needs. By contrast, the focus during adoption is establishing appropriate learning mechanisms to facilitate continuous learning. Thus, at individual level, willingness to learn is crucial.

The proposed framework shows the multi-faceted nature of successful digitalization projects, requiring multilevel enablers that span organizational, project, and individual levels. This interconnected perspective underlines the importance of an integrated, comprehensive understanding of the factors that leads to successful DT. This multilevel perspective offers a holistic understanding of DT, recognizing the integral role played by each level in managing digital initiatives. The framework also functions as a strategic guide, illuminating the soft factors organizations should prioritize for more effective implementation and adoption processes. By highlighting the necessity for multiple enablers at various levels, the framework enables organizations to strategically distribute their efforts, achieving a balanced approach to resource allocation. The framework also serves as a risk management tool, aiding in identifying potential risks across various levels within the organization.

Adopting this integrated multilevel approach can significantly enhance the success rate of DT projects, improving organizational efficiency and fostering an innovation culture. Moreover, the framework highlights several actions that should be implemented on the project level, including engaging end users for valuable insights, fostering effective communication, addressing team concerns promptly, ensuring managerial accessibility, regularly evaluating performance for continuous improvement, and promoting knowledge sharing. Also vital are keeping abreast with new requirements or regulations, engaging relevant stakeholders, ensuring robust project governance, fostering a trust-based environment, offering team members diverse experiences, providing proper mentorship, allowing space for experimentation, and delivering necessary training.

Each component contributes to creating an environment conducive to project success, enhancing team efficiency, morale, and fostering innovation. The findings underscore the significant role of individual team members in digitalization project success. Skills and knowledge, attitudes, motivation, and capacity for collaboration all influence the project's outcome. It highlights that understanding and leveraging these individual characteristics and providing necessary training can optimize team performance. The findings stress the importance of a human-centered approach, suggesting that technology alone is insufficient for successful DT; rather, the individuals implementing and using this technology play a vital role in driving these projects forward.

Furthermore, our findings relating to our two study objectives concur in the sense that the four core enablers that form the basis of the integrated framework are among the eight critical soft factors identified. We found learning to be the most critical factor. Although this finding is consistent with the findings of researchers who identify the building of know-how as an asset in the successful implementation of digitalization projects [12], we believe this is also attributed to other factors. One such factor could be that digitalization projects are not undertaken as a one-off initiative, unlike other projects, but as a part of or as one of the projects in the whole DT process [4]. For this reason, digitalization projects have greater potential to trigger organizational change while simultaneously requiring change [29]. Such changes require rethinking the entire workplace, including the development of new tasks, structures, skills, and capabilities, and therefore employees and managers should be encouraged to realize and seek to improve their capabilities and skills to be able to deliver the expected value in delivering the projects. These new requirements would influence the development of knowledge at all levels of the organization and further emphasize the need for continuous training of the people involved in projects.

6. Conclusion

This literature review has provided an in-depth exploration of factors that influence the implementation and adoption of digitalization projects, with a specific focus on the people dimension. To the best of our knowledge, this is the first systematic literature review that expounds the extent of available knowledge of success factors in the digitalization context and contrasts them at different organizational levels. The findings contribute to both research and practice through unveiling learning as the top critical success factor in DT context. In addition, a proposed framework is presented that highlights the multi-faceted nature of successful digitalization projects, requiring multilevel enablers that span organizational, project, and individual levels. The framework also highlight some difference and similarities between the two on project and individual levels that are worth noting.

On project level, the similarities are that both implementation and adoption require effective engagement with stakeholders, both emphasize proper communication channels and accessibility, and both value knowledge sharing and capacity building. For adoption case, this includes establishing knowledge sharing mechanisms while for implementation involves assigning appropriate mentors and providing training as needed. Differences at project level include; in implementation, the need for adequate project governance is emphasized. Furthermore, implementation projects place emphasis on creating a trustworthy project environment which involves building a space where team members feel safe, secure, and able to trust their colleagues. This is not specifically mentioned in the actions for successful adoption of digitalization projects. While experimentation is mentioned as an important action for successful implementation of projects, it is not specifically highlighted in the actions for successful adoption of digitalization projects. Whereas a clear emphasis is put on evaluating performance to identify areas for improvement in adoption, it is not explicitly mentioned for implementation projects although it is likely important as well.

On individual level, there are also some similarities and differences that are worth noting. Similarities include that both implementation and adoption demand a level of openness from the team members, highlight the importance of taking the initiative and underline the importance of a learning attitude and willingness to share knowledge or opinions. Differences are that for implementation, team members are required to be willing to take risks in an uncertain and dynamic environment. This might be due to the project's nature which could be more innovative or explorative, needing more tolerance for risks and uncertainty, team members in implementation projects are expected to have a personal motivation for growth and development. This might be significant in projects that necessitate continual learning and adaptation to new roles and tasks. In adoption, having proactive individuals who seek feedback and performance evaluations is important.

6.1 Future studies

Building from our review, we present areas for further studies:

- How do organizations ensure project manager readiness in the management of digitalization projects?
- How organizations strike a balance between knowledge exploitation and exploration in the DT context?
- What are competencies needed for DT at different organizational levels?

6.2 Limitations

This study is subject to some potential limitations. First, the different use of terminologies (i.e., digitalization projects, digital transformation projects, digitization projects) might have caused overlooking relevant publications. Second, we limited our searches to three databases which may have led to overlook publications in other databases. Third, given that the term “digitalization projects” has yet to gain much attention in the project management field, the identification of relevant publications might have been limited.

Conflict of interest

There is no potential conflict of interest with respect to this research.

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