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Big data driven supply chains in SMEs: The role of industry digitalization

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ABSTRACT

The adoption of technologies is critical for SMEs seeking to maintain competitiveness, particularly through improved supply chain management. While industry-level digitalization can either facilitate or constrain firm-level digitalization efforts, its role has received limited scholarly attention. This study investigates how the use of big data analytics in supply chain management is associated with SME profitability, and how this relationship varies by industry-level digitalization in terms of assets, usage, and labor. Drawing on survey data from 289 SMEs, supplemented with objective financial indicators and secondary data on industry digitalization, regression analysis reveals that the use of big data analytics in supply chain management significantly boosts SME profitability. The effect is most pronounced in industries characterized by high levels of digital stakeholder engagement (that is, usage), rather than other dimensions of digitalization. Our findings identify conditions under which investments in big data driven supply chains are most likely to yield financial returns.

KEYWORDS

Big data analytics; financial performance; digitalization; SMEs; supply chain management

Introduction

Digitalization has reshaped all industries (Garud et al., 2022; Giustiziero et al., 2023), yet small and medium-sized enterprises (SMEs) often lag behind (OECD, 2021). In SMEs, digitalization significantly enhances supply chain performance, more so than in larger enterprises (Justy et al., 2023; Liu et al., 2022; Merín-Rodrigáñez et al., 2024). As companies increasingly adopt technology to automate and optimize supply chain activities (Nguyen et al., 2018), big data analytics has emerged as a critical resource for managing competitive pressures (Centobelli et al., 2020; Chen et al., 2015; Dremel et al., 2017; Lamba & Singh, 2017; Schoenherr & Speier-Pero, 2015). This is especially true for

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business-to-business (B2B) companies, where complex, lengthy purchasing processes, such as tenders, require advanced technological tools.

While digitalization is widely studied, its complexity and impact on SMEs remain underexplored (Radicic & Petković, 2023). SMEs face unique challenges in digitalization due to limited resources (OECD, 2021), which can lead to outcomes that differ from those of larger companies (Setkute & Dibb, 2022). Most research on big data analytics focuses on large enterprises (Maroufkhani et al., 2020), leaving a gap in understanding its financial impact on SMEs. Additionally, industry-level digitalization can either support or hinder company-level initiatives, depending on the industry's digital maturity (Fernandez-Vidal et al., 2022). Despite its importance, industry-level digitalization, that is, how digitalization varies across industries, has received little scholarly attention (Aaldering & Song, 2021).

To address this gap, we draw on the resource-based view (Barney, 1991; Wernerfelt, 1984) to examine, first, how SMEs can enhance financial performance through big data analytics in supply chain management, and second, how different dimensions of industry digitalization shape this relationship. We analyze a data set of 289 SMEs operating in B2B markets. We combine data from three different sources: (1) a CEO survey (entrepreneurs and salaried managers) asking the extent to which their company uses big data analytics in supply chain management, (2) secondary company-level financial performance data for the year following the survey, and (3) a secondary measure describing industry digitalization.

The study aims to provide new insights into when big data analytics in supply chain management leads to improved financial performance in SMEs. Specifically, we examine whether big data analytics enhances profitability and how this effect is shaped by different dimensions of industry digitalization, namely physical IT investments (assets), digital engagement with customers and suppliers (usage), and digital engagement of employees (labor). Given SMEs' limited resources and the need to stay competitive against larger enterprises (Saura et al., 2023; Vaaland & Heide, 2007), understanding these conditions is crucial for SME managers. By recognizing how various aspects of digitalization affect outcomes, SME managers can better prioritize digital investments, reduce the risks associated with big data analytics adoption, and allocate resources more strategically to support the building of data-driven supply chains.

This study makes four key contributions to the literature on SME digitalization (Cannas, 2023; Proksch et al., 2021; Radicic & Petković, 2023). First, given that the prior literature argues that the performance implications of big data analytics may be more significant for SMEs than for larger companies (Dong & Yang, 2020), and that future research should focus on identifying factors that help SMEs to benefit from big data analytics, as they tend to lag in adopting new technologies (Maroufkhani et al., 2023), we explore the performance outcomes of big data analytics in SMEs' supply chain management. The findings contribute to recent research that emphasizes the importance of supply chain management in SMEs for improving their competitive advantage (Son et al., 2019; Sukwadi et al., 2013). Second, the study adds to the discussion about the conditions (Oduro et al., 2023; Vitari & Roguseo, 2020) under which big data analytics results in increased profitability. Although we show that companies benefit from big data analytics in supply chain management, this effect varies depending on the level and type of digitalization in the industry in which the company operates. Third, while the existing research (De Luca et al., 2021) has focused on the impacts of digitalization at an aggregate level, we emphasize how different dimensions of industry digitalization transform the financial outcomes achievable through big data analytics. This enables more fine-grained insights into the impact of industry digitalization. Fourth, in response to Vitari and Roguseo (2020), who emphasized the importance of using multiple sources of data, we jointly use survey data and secondary data sources to reevaluate and verify the direct impact of big data analytics on profitability, with a specific focus on SMEs operating in B2B markets.

The remainder of this article is structured as follows. The next section introduces the research model, which is grounded in existing theory and literature. We then describe the research methodology, including data collection and construct validation. This is followed by the results of the data analysis and a discussion of the findings in relation to prior research. We conclude by outlining theoretical and managerial implications, acknowledging limitations, and suggesting directions for future research.

Theoretical background and model development

The present study builds on the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984) and the subsequent resource-based theory (see, for example, Galbreath, 2005; Pereira & Bamel, 2021; Seddon, 2014; Wade & Hulland, 2004; Zhang et al., 2021), according to which companies possess a multitude of resources, which can enable them to achieve superior performance and long-term competitive advantage. Therein, a resource is any strength that a company possesses, with resources commonly comprising procedures, assets, attributes, capabilities, knowledge, and competencies that are internal to the company (Barney, 1991). Resource-based theory states that a company possesses a variety of valuable tangible and intangible resources that can be used to gain a competitive advantage (Peteraf, 1993), and that information systems resources represent one of the most fundamental assets in this regard (Ravichandran et al., 2005).

Originally, resources were defined under resource-based theory as unique, rare, and company-specific assets that allow a business to carry out a value-creating strategy (Barney, 1991; Wernerfelt, 1984). Fundamentally, big data consists of large-scale and complex data sets stemming from various sources and structures that cannot be processed with conventional analysis methods (Bharadwaj et al., 2013). Additionally, big data is typically described in terms of characteristics such as volume, variety, velocity, and veracity (Ghasemaghaei & Calic, 2019). Pertinent to the original definitions of the resource-based theory, big data represents a rare, inimitable, and non-substitutable resource for a company because relevant data may be hard to identify, and every company needs to build a unique configuration to acquire value and key insights from it. Big data can be considered a non-imitable and non-substitutable resource, because companies seldom reveal their data resources to external parties, and overall, the data are well protected within the company's information systems to avoid leakages. Further research has distinguished between two underlying causal mechanisms in building competitive advantage: capability building and resource picking (Makadok, 2001). The fundamental premise of the latter mechanism is that companies create competitive advantage by being more effective than competitors at *selecting* resources, while the former mechanism postulates that companies build economic value by being more effective than competitors at *deploying* resources (Makadok, 2001). In terms of big data analytics, competitive advantage is dependent on both capability building and resource picking. Companies must be able to select and configure their data and tools for collecting, analyzing, and storing data to use them to improve their operations. However, as with digital technologies more broadly, merely acquiring the assets is just the first step toward competitive advantage; the real value depends on how these assets are used to improve various business processes.

Big data analytics in supply chain management

In today's dynamic business environment, competition is shifting from individual companies to entire supply chains (Li et al., 2006). However, supply chains have become increasingly complex as companies are forced to cope with resource deficiencies due to environmental uncertainties (Tunisini et al., 2023). In this transformation, companies are forced to adopt new approaches for more effective supply chain management to achieve a competitive advantage (Centobelli et al., 2020; Li et al., 2006; Son et al., 2019; Sukwadi et al., 2013). Boosted by digitalization, companies are increasingly utilizing sensors, barcodes, radio frequency identification (RFID), and the Internet of Things (IoT) in their supply chain management (Boyson et al., 2022; Nguyen et al., 2018), generating large volumes of big data. Consequently, as the volume of data generated from supply chain management activities has grown at a rapid rate (Tiwari et al., 2018), big data analytics is gaining momentum in supporting supply chain management activities (Centobelli et al., 2020; Dremel et al., 2017; Lamba & Singh, 2017). Big data analytics allows companies to build intelligent vendor selection systems, forecast business trends, and anticipate product demand, which reduces risks in manufacturing and results in enhanced logistics and inventory management (Lamba & Singh, 2017; Li et al., 2015; Wang et al., 2016). This enables greater supply chain visibility and flexibility, and more efficient allocation of resources (Frizzo-Barker et al., 2016; Sivarajah et al., 2017).

The anticipated financial benefits and potential to improve customer satisfaction provide persuasive arguments for the adoption of big data analytics in supply chain management (Raman et al., 2018). This is supported by recent literature, according to which big data analytics in supply chain management enables companies to achieve positive financial outcomes (Bahrami & Shokouhyar, 2022; Chen et al., 2015; Dubey et al., 2019; Gunasekaran et al., 2017). For instance, a study among supply chain managers ($n = 173$) in Indian auto component companies reported that big data analytics capability has a positive and significant effect on supply chain agility and competitive advantage (Dubey et al., 2019). Elsewhere, a study by Bahrami and Shokouhyar (2022) supports this, as they found that big data analytics capability has a positive effect on financial performance based on 167 responses from IT executives in Iranian companies. A study among 161 U.S.-based companies similarly reported that company-level big data analytics drives organizational value creation (Chen et al., 2015), while a study among heads of supply chain management operations ($n = 205$) reported that big data predictive analytics assimilation positively correlates with supply chain performance and organizational performance (Gunasekaran et al., 2017). However, Saleem et al. (2021) demonstrated that the effect of big data analytics on SME performance and supply chain performance is not necessarily direct. They discovered that product and process innovation mediate the relationships, while information sharing strengthens them. This finding contrasts with prior research reporting a direct association (for example, Akter et al., 2016), and therefore, we examine whether industry-related differences account for these variations, which we later address in hypothesis 2.

Efficient supply chain management has become increasingly critical for firms' competitiveness as market demands intensify and environmental uncertainties create resource constraints (Tunisini et al., 2023). For SMEs, this challenge is even more pressing. Vaaland and Heide (2007) concluded that SMEs are at risk of losing competitiveness to larger firms because they are slower to adopt new technologies that improve their supply chain management. However, we argue that SMEs' greater agility and ability to rapidly respond to data-driven insights make big data analytics particularly effective in enhancing their supply chain management. Big data analytics enables more accurate demand forecasting, optimizes inventory levels, accelerates exception handling, and strengthens supplier coordination. These mechanisms directly reduce operational costs, protect revenues, and improve capital efficiency.

Within the framework of RBV, such a capability is expected to contribute to superior financial outcomes and foster sustainable competitive advantage. Grounded in the core principles of RBV and supported by the majority of the existing big data analytics financial performance literature (Bahrami & Shokouhyar, 2022; Chen et al., 2015; Dubey et al., 2019; Gunasekaran et al., 2017), we expect that big data analytics in supply chain management will foster SME performance. We hypothesize that:

Hypothesis 1: *Big data analytics in supply chain management positively relates to profitability.*

Industry digitalization

In recent years, digitalization has become a buzzword in the corporate world, presenting both opportunities and challenges for SMEs (Gartner et al., 2022; Thrassou et al., 2020). Fundamentally, digitalization has changed and disrupted established industries (Gala & Mueller, 2022), and consequently, digital business transformation has forced companies to develop their foundational capabilities to remain competitive (Cannas, 2023; Wielgos et al., 2021). It is relatively well established that specific industries are more digitally advanced and possess fundamentally better IT capabilities than others (Bharadwaj et al., 1999; Stoel & Muhanna, 2009), which helps to explain performance variation (Aral & Weill, 2007). At the same time, specific industries tend to encounter stronger technological turbulence (Autry et al., 2010; Chen et al., 2015), which requires them to keep up to date with emerging technologies, including big data analytics.

To examine the impact of digitalization in greater detail, we build our exploration upon Gandhi et al. (2016), categorizing industry digitalization into three subdimensions: assets, usage, and labor. This categorization is reminiscent of classical categorizations used in the information systems literature (Ross et al., 1996), according to which technology assets, human assets, and relationship assets in combination constitute a company's IT capability, and they jointly form the basis for IT-driven competitive advantage. In the context of digitalization, *assets* encompass computer hardware, software, data, and IT services, consisting of both digital asset stock and digital spending (Gandhi et al., 2016). In this study, assets refer to the physical IT assets, which form the core of the overall IT infrastructure (Bharadwaj, 2000). Digital *usage* measures the extent to which companies in different industries engage digitally with their stakeholders, taking into consideration that companies in the leading sectors make more extensive use of digital opportunities, including digital payments and digital marketing (Gandhi et al., 2016). The third dimension, *labor*, emphasizes the human role in digital transformation and reflects the degree to which employees engage with digital technologies to enhance productivity (Gandhi et al., 2016). It is noteworthy that industries with the same level of overall digitalization may have notable variations across the three subdimensions (Gandhi et al., 2016). For instance, wholesale trade, advanced manufacturing, and the oil and gas industry share the same overall digitalization score. While wholesale excels in the digitalization of assets, advanced manufacturing leads in the digitalization of usage, whereas the oil and gas industry stands out in the digitalization of labor. Understanding this variation is crucial because all three industries are digitalized, albeit in different ways.

There are considerable differences in returns from big data analytics in different industries, as emphasized, for example, by Müller et al. (2018). A company's ability to obtain business value from big data analytics is known to vary depending on environmental uncertainty (Laguir et al., 2022) and contextual factors (Mikalef & Krogstie, 2020). To create business value from big data analytics, firms must overcome barriers related to data, processes, and management, including infrastructure, data quality, analytical skills, data culture, and resource integration (Alharthi et al., 2017; Sivarajah et al., 2017). In general, companies operating in more digitally advanced industries are better equipped to overcome technology-related challenges and leverage big data analytics. Our reasoning stems from the logic that a company's investments in big data analytics––particularly its usage and the engagement of employees in uniting business and technology around a common goal (Kiron et al., 2014)––generate experiences and knowledge that, consistent with the resource-based view (Barney, 1991), foster superior performance. This is supported by De Luca et al. (2021), who find that big data investments yield greater returns in highly digitalized industries.

We expect that each subdimension of industry digitalization strengthens the relationship between big data analytics and financial performance, though they do so differently. Companies operating in industries with high digitalization of assets are likely to possess a stronger data infrastructure and have greater experience in managing diverse data sources, as they invest more in digital technologies and maintain a larger digital asset stock. A powerful computational data infrastructure is needed to adequately capture, store, and analyze big data (Alharthi et al., 2017). Consequently, we expect that the positive effect of big data analytics in supply chain management on profitability is more pronounced for companies that operate in industries with higher levels of digitalization of assets (H2a).

Companies in industries with high digitalization of usage are likely to generate larger and more diverse amounts of data from their daily operations and implement effective data-sharing policies as they handle transactions, interactions, business processes, and market-making activities more digitally. Fundamentally, big data is described as high-volume, high-velocity, and high-variety data, and each aspect of big data is equally essential for generating business value from big data analytics. Using digital systems in daily operations creates high-quality and consistent data in real-time. Such data quality and consistency are crucial for drawing reliable conclusions from analytics to support decision-making (Alharthi et al., 2017). An open data-sharing culture also fosters business value derived from big data analytics (Eastwood, 2021). Hence, we expect that the positive effect of big data analytics in supply chain management on profitability will be stronger for companies operating in industries with higher levels of digitalization of usage (H2b).

Finally, companies operating in industries with high levels of digitalization of labor are expected to possess stronger data skills and a more developed data culture, as higher digital spending on employees, digital capital deepening, and digitization of work (Gandhi et al., 2016) foster these capabilities. Erevelles et al. (2016) suggested that investments in human capital resources, as well as in organizational resources, are necessary to fully leverage big data. Employees' analytics skills, along with the data culture of the organization, influence how effectively knowledge derived from big data analytics is interpreted and applied in decision-making (Alharthi et al., 2017). Therefore, we expect that the positive effect of big data analytics in supply chain management on profitability will be stronger for companies that operate in industries with a higher level of digitalization of labor (H2c).

We hypothesize that the three dimensions of industry digitalization enhance a company's ability to leverage big data analytics in supply chain management to improve profitability. Figure 1 illustrates our research model.

Hypothesis 2: *The positive effect of big data analytics in supply chain management on profitability is stronger for companies that operate in industries with*

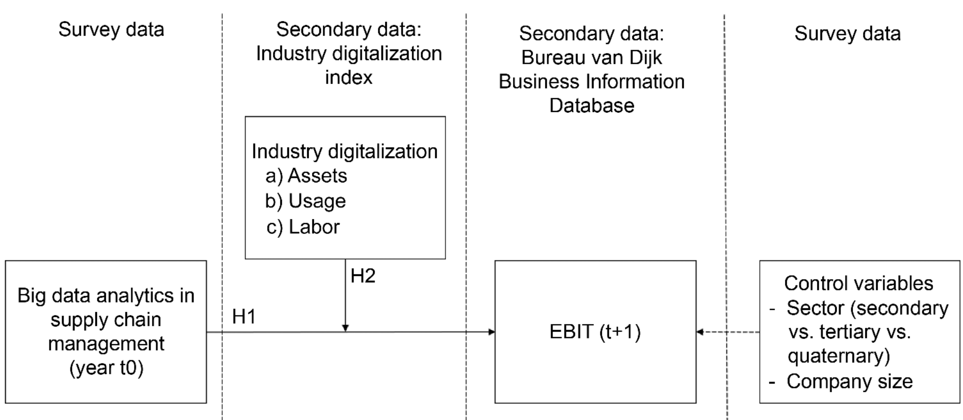

Figure 1. Research model.

a greater level of digitalization. This holds for the digitalization of assets (H2a), usage (H2b), and labor (H2c).

Research method

Data collection and sample

Our exploration focuses on SMEs with an employee count ranging from 10 to 250 employees (European Commission, 2022). It is important to understand the use of big data analytics in SMEs, considering that big data analytics holds significant potential for them (Dong & Yang, 2020; Maroufkhani et al., 2023). Micro-enterprises were not included because SMEs are more likely than micro-enterprises to use big data analytics. The empirical study combines data from three different sources to examine how industry digitalization interacts with big data analytics in supply chain management to enhance profitability. We believe that the combined use of survey and secondary data sources provides a more objective view of the interrelationship between big data analytics and profitability, and reduces concerns related to the common method bias (Podsakoff et al., 2012). We used survey data that measures the use of big data analytics in supply chain management among B2B SMEs across various industries in Finland. The data collection followed census procedures, and for the purpose of the study, we contacted a private corporate information company and ordered a nationwide listing of all Finnish companies with an employee count ranging from 10 to 250 employees, including a contact email address for each company. We distributed an online questionnaire to the head of the company (salaried manager or entrepreneur), and in collecting the data, we emailed invitations in three data collection waves with appropriate reminders (for example, Dillman et al., 2014). Participation in the survey was voluntary and uncompensated. The final sample comprises 289 responses from salaried managers and entrepreneurs in SMEs operating in B2B markets. Table 1 illustrates respondent characteristics, and Table 2 shows the distribution of the company characteristics in the data set.

Table 1. Respondent characteristics.

	Frequency	Percent
Age (Mean)	34	
Gender		
Female	31	10.7
Male	258	89.3
Job level		
Top- or middle-level management	234	81.0
Entrepreneur	55	19.0

Table 2. Company characteristics.

	Structure of the research data		Company structure in Finland*	
	Frequency	Percent	Frequency	Percent
Size (Number of employees)				
Small (10–49 employees)	216	74.7	16910	82.2
Medium (50–249 employees)	73	25.3	3017	14.6
Industry and sector				
Secondary sector (finished goods)				
10–33 Manufacturing	87	30.1	3495	17.0
35 Electricity, gas, steam, and air conditioning	9	3.1	170	0.8
41–43 Construction	46	16.0	3305	16.1
Tertiary sector (service sector)				
45–47 Wholesale and retail trade	32	11.1	3571	17.3
49–53 Transportation and storage	16	5.5	1540	7.5
55–56 Accommodation and food service	1	0.3	1079	5.2
58–63 Information and communication	7	2.4	1202	5.8
64–66 Finance and insurance	1	0.3	391	1.9
68 Real estate	12	4.2	317	1.5
Quaternary sector (knowledge economy)				
69–75 Professional, scientific, and technical activities	39	13.5	1705	8.3
77–82 Administrative and support services	16	5.5	1625	7.9
84 Public administration	3	1.1	–	–
85 Education	2	0.7	107	0.5
86–88 Human health and social work	5	1.7	948	4.6
90–93 Arts, entertainment, and recreation	2	0.7	236	1.1
Other				
94–96 Other services	11	3.8	184	0.9

*Statistics extracted from Statistics Finland website at: http://pxnet2.stat.fi/PXWeb/pxweb/en/StatFin/StatFin__yri__yrti__oik/statfin_yrti_pxt_11qe.px/ and https://www.tilastokeskus.fi/tup/suoluk/suoluk_yritykset.html.

Independent variable: Big data analytics

We set up a survey study to measure the extent to which the focal company utilizes big data analytics in supply chain management. We measured big data

Table 3. Scale properties.

	Mean	Std. deviation	Factor loading
Big data analytics (Schmarzo, 2013)			
1. We use big data to identify which suppliers are most cost-effective in delivering products on time and without damage.	2.000	1.102	0.677
2. We use big data to flag machinery and process variances that might be indicators of quality problems.	2.173	1.241	0.805
3. We use big data to optimize merchandise markdown based on current buying patterns, inventory levels, and product interest insights gleaned from social media data.	1.772	0.994	0.683
Industry digitalization index (Gandhi et al., 2016)			
Digitalization of assets			
1. Digital spending	2.962	1.892	0.999
2. Digital asset stock	3.775	1.375	0.876
Digitalization of usage			
1. Interactions	3.228	1.487	0.677
2. Business processes	3.772	1.232	0.978
3. making	3.893	1.060	0.944
Digitalization of labor			
1. Digital spending on workers	3.495	1.446	0.899
2. Digital capital deepening	3.353	1.650	0.996
3. Digitization of work	3.087	1.827	0.939

analytics using a construct with three measurement items based on Schmarzo (2013). The three-item scale focuses on supplier effectiveness, quality issues, and merchandize optimization (Table 3). Operationalization is fundamentally meant to capture the differences in the extent of big data analytics implementation between companies, and not different technologies nor capabilities that pertain to big data analytics use, per se. The measurement scale for big data analytics ranged, on a five-point Likert scale, from 1, indicating *little or no usage*, to 5, indicating *strong usage*.

Dependent variable: Earnings before interest and tax (EBIT)

We obtained our dependent variable, earnings before interest and tax (EBIT), for the year that followed the data collection (year $t + 1$) from the external business information database, Amadeus (2025) (renamed Orbis Europe). The Amadeus database contains comparable financial information for public and private companies across Europe, drawing financial performance data from their official financial statements. The dependent variable, EBIT in year $t + 1$, represents a company's financial performance in the year that followed the survey data collection. We used an accounting performance measure (Katsikeas et al., 2016) for financial performance instead of a stock market value measure, such as Tobin's Q, because, unlike the majority of big data analytics studies published so far, our data represent only SMEs.

Moderating variable: Industry digitalization

We based the operationalization of industry digitalization on a secondary study by Gandhi et al. (2016), which explored the extent to which different industries are digitalized in relation to other industries in three subcategories: digital assets, usage, and labor. In their digitalization index, Gandhi et al. (2016) categorized industries on a scale ranging from 1 = weakly influenced by digitalization to 6 = highly influenced by digitalization related to three main categories: digital assets, digital usage, and digital labor. Contrary to earlier academic studies (Edeling & Himme, 2018; Wielgos et al., 2021), we deployed the industry digitalization index in its original six-point scale to capture variance more effectively. In the present study, we used a standard NACE industry classification of each company and assigned them an industry digitalization score corresponding to the three subareas of industry digitalization (Gandhi et al., 2016).

Construct validation

We performed a confirmatory factor analysis (CFA) to establish a measurement model and to validate the research constructs in the given context. The CFA model comprises 12 variables assigned to four multiple-item latent constructs, namely big data analytics use, digitalization of assets, digitalization of usage, and digitalization of labor (Table 3). In CFA, the first item of digitalization of usage (transactions) indicated a weak loading on its intended factor, and the construct also indicated high between-construct correlations with related constructs. Consequently, we excluded the first item of digitalization of usage, after which the model shows an adequate fit ($\chi^2 = 1072.305$ (df = 38), $p < .001$, CFI = 0.946) and indicates no concerns regarding convergent and discriminant validity (Table 4).

Müller et al. (2018) emphasized that future research should examine differences in how big data analytics impacts business outcomes in greater detail. Therefore, we used industry sector (secondary vs. tertiary vs. quaternary) and company size as control variables.

Results

Main study

We tested the hypotheses using stepwise regression in Mplus 8.6 (Table 5). Model 1 serves as the baseline, assessing the main effect of big data analytics in supply chain management on EBIT among B2B SMEs (H1), without other variables. Models 2–4 address H2 by introducing interaction between big data analytics and each dimension of industry digitalization (assets, usage, and labor). Model 5 includes all interaction terms simultaneously, and Model 6 adds control variables. Model 1 shows that big data analytics in supply chain management has a statistically significant positive relationship with profitability ($\beta = 0.071$, $p = .006$), which supports hypothesis H1. Models 2–4 add the interaction of industry digitalization one dimension at a time. Model 2 shows no support for the interaction of the digitalization of assets ($\beta = 0.041$, $p = .407$), and thus, we reject H2a. The digitalization of usage has a marginally significant positive relationship between big data analytics and profitability with $\beta = 0.078$ ($p = .074$), providing marginal support for H2b, while the interaction of the digitalization of labor is statistically non-significant ($\beta = 0.052$, $p = .305$), rejecting H2c. Model 5 includes the three dimensions of industry digitalization simultaneously, which strengthens the interaction of big data analytics and digitalization of usage further to $\beta = 0.086$ ($p = .005$).

Table 4. Discriminant validity.

	CR	AVE	1	2	3	4
1. Big data analytics	0.767	0.524	**0.724**			
2. Digitalization of assets	0.937	0.883	**−0.268**	**0.940**		
3. Digitalization of usage	0.907	0.769	−0.137	0.563	**0.877**	
4. Digitalization of labor	0.962	0.894	−0.226	0.893	0.666	**0.946**

Table 5. Results of the main study.

Dependent variable: EBIT in year *t*+1	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Independent variable	Coeff.	*p*	Coeff.	*p*	Coeff.	*p*	Coeff.	*p*	Coeff.	*p*	Coeff.	*p*
Big data analytics	0.071	.006	0.084	.014	0.093	.006	0.085	.011	0.090	.012	0.062	.072
Moderating variable												
Digitalization of assets			0.042	.471					−0.037	.374	0.135	.091
Digitalization of usage					0.080	.116			0.098	.003	0.012	.756
Digitalization of labor							0.049	.412	0.013	.796	−0.025	.626
Interaction term												
Big data analytics x Digitalization of assets			0.041	.407					−0.051	.283	−0.050	.253
Big data analytics x Digitalization of usage					0.078	.074			0.086	.005	0.075	.014
Big data analytics x Digitalization of labor							0.052	.305	0.040	.451	0.056	.269
Control variables												
Secondary sector											0.023	.588
Tertiary sector											−0.106	.013
Quaternary sector											0.011	.894
Company size											0.185	.019

Examination of the control variables (Model 6) shows that the effects of the tertiary sector and company size are statistically significant on EBIT.

While H2b only marginally approaches statistical significance (at the 90 percent confidence level) when digitalization of usage is alone in the model (Model 3), Figure 2 illustrates the interaction of the digitalization of usage on the path between big data analytics and profitability (H2b) using the Johnson–Neyman approach. The lower confidence interval crosses the zero-line at the value of 5, indicating that the interaction of digitalization of usage is statistically significant for digitalization values lower than 5, and it becomes statistically non-significant with digitalization values greater than 5.

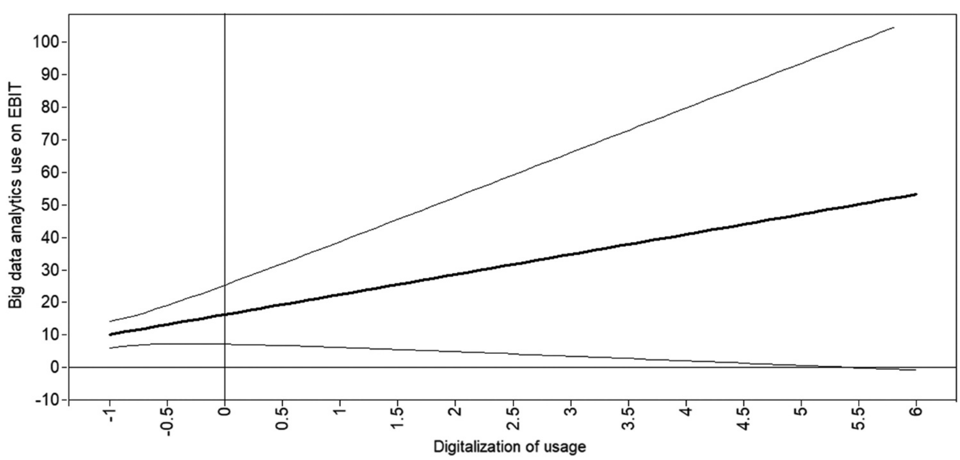

Figure 2. Interaction of digitalization of usage on the path between big data analytics and profitability.

Table 6. Results of the robustness test.

Dependent variable: EBIT in year t+1	Model 1		Model 2	
Independent variable	Coeff.	*p*	Coeff.	*p*
Big data analytics	0.021	.001	0.061	.022
Moderator variable				
Digitalization of assets			−0.231	.062
Digitalization of usage			0.214	.035
Digitalization of labor			0.022	.641
Interaction term				
Big data analytics x Digitalization of assets			−0.165	.116
Big data analytics x Digitalization of usage			0.171	.079
Big data analytics x Digitalization of labor			−0.011	.803

Robustness test

To ensure the validity and comprehensiveness of our results, we tested the robustness of our findings using an additional dataset ($n = 141$ companies), collected from companies listed in the Amadeus database (Table 6). Consistent with the procedures of our main study, we used the Amadeus database to provide a nationwide listing of all Finnish companies with 10–250 employees. A link to the questionnaire was sent to the company head's individual email address; if the individual email address was unavailable, the survey was directed to a general company email with a request to forward the link to the CEO. The survey was delivered to a total of 9,101 participants. By the end of the four-week research period, we received 141 completed questionnaires, resulting in a response rate of 1.6 percent. The same measurement items used in the main study were employed to assess the use of big data analytics in supply chain management. The sample includes Finnish companies with employee numbers ranging from 10 to 250. Similarly, as in our main study, we supplemented the survey data set with EBIT in year $t + 1$ from the Amadeus database (2025). A robustness test shows consistent results with the findings of our main study, with big data analytics as a sole variable demonstrating a highly significant relationship with EBIT ($\beta = 0.021$, $p = .001$). Aligned with the results of our main study, the interaction of digitalization of usage is positive and marginally significant with $\beta = 0.171$ ($p = .079$). Consistent with the main study's results, the interactions of digitalization of assets and digitalization of labor do not significantly influence the relationships between big data analytics and EBIT.

Discussion

This study explores how big data analytics in supply chain management impacts SME financial performance and identifies the industry-level conditions that enhance these outcomes. Our findings show that big data analytics implementation significantly improves profitability in SMEs, supporting managerial expectations highlighted in prior research. However, the benefits vary depending on the level and type of industry digitalization. Specifically, big data analytics has a stronger positive effect in industries with high usage-related digitalization, that is, industries characterized by digital transactions, interactions, business processes, and market-making. This suggests that SMEs benefit most from big data analytics when operating in industries with high levels of digital interaction with suppliers and customers. As Proksch et al. (2021) noted, digital process transformation is supported by both digital IT capabilities and digital culture. To maximize the impact of big data analytics, SMEs should focus on integrating digital tools across the value chain. For example, utilizing digital payments and e-commerce platforms, digital marketing, and software for business and customer relationship management will increase usage-related digitalization (Gandhi et al., 2016) and thus enhance performance outcomes of big data analytics.

However, asset-related industry digitalization does not influence the relationship between big data analytics and profitability. This dimension reflects companies' investments in digital technologies and overall digital asset stock. Our findings align with Gandhi et al. (2016), who argued that competitive advantage depends primarily on how digital assets are utilized and how employees engage with them. Surprisingly, we also found no support for the moderating effect of labor-related digitalization, which includes digital investment in workers, digital capital deepening, and work digitization. This suggests that labor-related digitalization does not enhance the financial returns from big data analytics, at least not in the short term, despite being identified by Gandhi et al. (2016) as a key driver of competitive advantage. Given that employees are a critical resource and that data skills and culture are major challenges (Alharthi et al., 2017), this result may differ over a longer time horizon, offering a promising direction for future research.

Theoretical contributions

This study contributes to the SME digitalization literature (Cannas, 2023; Proksch et al., 2021; Radicic & Petković, 2023) in several ways. First, it contributes to research framing big data analytics as a strategic IT resource for performance improvement (Hallikainen et al., 2020; Li et al., 2022; Merendino et al., 2018). While the financial impact of big data analytics may be greater for SMEs than for larger enterprises (Dong & Yang, 2020), most prior research has focused on large enterprises (Maroufkhani et al., 2020). Accordingly, we responded to Maroufkhani et al. (2023) by identifying industries and conditions where SMEs can benefit from big data analytics. Given SMEs' slower adoption of advanced digital technologies (OECD, 2021), our findings offer important evidence on the performance implications of big data analytics in SMEs. Specifically, we highlight its role in supply chain management, a function increasingly recognized as critical to SME competitiveness (Son et al., 2019; Sukwadi et al., 2013).

Second, this study advances the understanding of the conditions under which big data analytics in supply chain management enhances financial performance. While prior research has emphasized the role of internal big data analytics capabilities (Gupta & George, 2016; Hossain et al., 2022), less attention has been paid to external factors shaping the big data analytics–performance link (Vitari & Raguseo, 2020). Responding to Aaldering and Song's (2021) call for more focus on industry-level digitalization, our key contribution lies in showing how this broader context moderates the impact of big data analytics. Drawing on the resource-based view, we demonstrated that industry digitalization, measured using the industry digitalization index (Gandhi et al., 2016), influences the financial returns from big data analytics. This builds on recent studies (for example, Edeling & Himme, 2018; Wielgos et al., 2021) and aligns with longstanding efforts to understand digital leaders and laggards (Aaldering & Song, 2021; Smith, 2014).

Third, this study adopts a more nuanced approach following Gandhi et al. (2016), to capture a broader variance in industry digitalization, whereas prior research has generally relied on a low-versus-high categorization for industry digitalization (for example, in Edeling & Himme, 2018; Wielgos et al., 2021). Additionally, we distinguish between asset-, usage-, and labor-related digitalization to show how each dimension shapes the performance impact of big data analytics in supply chain management. To our knowledge, this is the first study to fully apply this three-dimensional approach to industry digitalization, enabling more fine-grained insights into how big data analytics creates value. This approach deepens our understanding of the specific industry-level drivers that enhance the effectiveness of big data analytics for SMEs.

Fourth, most big data analytics research relies on surveys and self-reported financial metrics, which have known limitations (Hulland et al., 2018). Our study strengthens this body of work by combining survey data with externally validated financial performance data, focusing on SMEs in B2B markets. By using objective profitability measures, we enhance the reliability of our findings. This integration of subjective and objective data adds a critical layer of verifiability to the ongoing discussion on the role of big data analytics in financial company performance and extends research to the effects of digitalization.

Managerial implications

The findings of this study are particularly relevant for SME managers, as we provide some of the first empirical evidence linking big data analytics use in supply chain management to objective financial performance in SMEs. This helps SME managers to justify investments in big data initiatives by clarifying the conditions under which big data analytics delivers financial returns. Specifically, SMEs in industries with high usage-related digitalization, such as ICT, media, finance, and insurance, benefit more from big data analytics than those in less digitally engaged sectors such as agriculture, construction, or government. This highlights the importance of leveraging digital technologies to facilitate interactions and transactions across the supply chain. Companies that engage digitally with their supply chain partners generate more diverse and voluminous data, enabling better decision-making. As Guesalaga et al. (2018) noted, digital capabilities and knowledge are developed through complex, interactive processes between different stakeholders in the supply chain, involving mechanisms that are difficult for competitors to replicate. Thus, SMEs can fully harness the value of big data analytics by deepening digital engagement across their supply chains.

However, the findings suggest that investments in digital assets alone may not be sufficiently rare to create a competitive advantage. As digital technologies and big data analytics tools become more accessible and affordable for SMEs, simply acquiring them is no longer enough to generate value. The associated learning may be technical and easily replicable, reducing its strategic impact. Competitive advantage stems more from how these technologies are integrated into daily operations than from the investments themselves. Similarly, labor-related investments, such as employee training in digital tools, are costly and may not directly translate into financial gains. Their benefits may appear in qualitative performance measures (Popova & Sharpanskykh, 2010), which are harder to quantify. Moreover, knowledge loss due to employee turnover limits the viability of such investments. Ultimately, our findings underscore the value of big data analytics in SME supply chain management and guide leaders in prioritizing digital initiatives that most effectively enhance profitability.

Limitations and future research

This study focused specifically on the use of big data analytics in supply chain management, excluding other business applications. It was conducted using data from Finnish B2B SMEs, which may limit the generalizability of the findings to other regions, larger enterprises, or consumer-facing businesses. Future research could explore the impact of big data analytics across different business functions or test the proposed model in larger companies to broaden its applicability. Unlike many prior studies relying solely on survey data and cross-sectional designs, this study combined survey responses with secondary financial performance data. While the use of objective profitability metrics is a key strength, the analysis is limited to direct effects, suggesting opportunities for future research to explore indirect or long-term impacts.

In this study, we used the industry digitalization index (Gandhi et al., 2016) to examine the moderating effect of industry digitalization. While the index is based on U.S. industries and our data come from Finnish companies, we consider the potential bias minimal, as both countries are developed, market-driven economies with advanced digital infrastructure and similar industry characteristics. To obtain objective digitalization data, we measured digitalization at the industry level, while big data analytics and profitability were assessed at the company level. Although this introduces a potential mismatch, we argue that industry-level measurement is appropriate in the context of big data-driven supply chains, where companies rely on data from various supply chain players in the industry, not only their own systems. We also encourage future research to further explore the classification of industry digitalization into asset-, usage-, and labor-related dimensions, and to combine multiple data sources to reduce common method bias (Podsakoff et al., 2012).

Conclusion

This study advances research on the impact of digitalization in SMEs. While prior work has explored big data analytics in supply chain management, the role of industry digitalization remains underdefined, particularly in the SME context, which is often overshadowed by studies on large enterprises. Grounded in the resource-based view (RBV), we examined how industry digitalization moderates the relationship between big data analytics in supply chain management and profitability in SMEs. Our findings confirm that big data analytics enhances SME profitability. Moreover, the benefits are significantly greater in industries with high usage-related digitalization, while asset- and labor-related digitalization show no such effect. These findings offer valuable insights into the conditions under which big data analytics delivers financial benefits for SMEs, helping managers better prioritize digital investments. SMEs in highly digitalized industries, such as ICT, media, finance, and insurance, where customer and supplier interactions are largely digital, are more likely to benefit from big data analytics in supply chain management. As the results highlight disparities driven by industry digitalization, they also offer guidance for policymakers to help bridge the digital divide and support less digitalized sectors in realizing the benefits of digital transformation. Overall, the study underscores the importance of effective digital engagement—such as digital marketing, e-commerce platforms, and digital payments—across the supply chain. In contrast, investments in digital assets or workforce digital tools alone appear less effective for improving financial performance through big data analytics.

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