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THE RELATIONSHIP BETWEEN BIG DATA CAPABILITY AND BUSINESS PERFORMANCE: THE MEDIATING ROLE OF SUPPLY CHAIN FLEXIBILITY AND THE MODERATING ROLE OF ENVIRONMENTAL UNCERTAINTY

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Abstract

In this study, it was aimed to determine the effect of Big Data Capability (BDC) on Business Performance (BP) and the mediating role of Supply Chain Flexibility (SCF) and the moderating role of Environmental Uncertainty (EU) in this effect. The universe of the research consists of businesses that benefit from digital technologies in their supply chain processes in Turkey. An online questionnaire was applied to 301 middle and senior managers reached by convenience sampling method; the data were analyzed by Structural Equation Modeling (SEM). The values for the measurement model (CFI=0.999, TLI=0.998, RMSEA<0.08) were perfectly agreed. The findings revealed that BCD had a positive and significant effect on SCF (β=0.483, p<0.001). SCF strongly affects BP (β=0.734, p<0.001), whereas the direct effect of BDC on BP was found to be insignificant (β=0.038, p=0.348). Since the indirect effect was significant (β=0.355, p<0.001), it was determined that SCF played a full mediating role in this relationship. In addition, EU has been found to have a moderator effect that weakens the relationship between BDC and SCF (β=−0.155, p=0.004). As a result, BDC does not directly increase BP; however, it develops indirectly through SCF.

Keywords: Big Data Capability, Supply Chain Flexibility, Environmental Uncertainty, Business Performance, Structural Equation Modeling
JEL Classification: M11, M15, L25, O33, C38

BÜYÜK VERİ YETKİNLİĞİ İLE İŞ PERFORMANSI ARASINDAKİ İLİŞKİ: TEDARİK ZİNCİRİ ESNEKLİĞİNİN ARACILIK ROLÜ VE ÇEVRESEL BELİRSİZLİĞİN DÜZENLEYİCİ ROLÜ

Öz

Bu çalışmada, Büyük Veri Yetkinliğinin (BVY) İşletme Performansı (İP) üzerindeki etkisi ve bu etkide Tedarik Zinciri Esnekliğinin (TZE) aracılık, Çevresel Belirsizliğin (ÇB) ise düzenleyici rolünün belirlenmesi amaçlanmıştır. Araştırmanın evrenini Türkiye'de tedarik zinciri süreçlerinde dijital teknolojilerden yararlanan işletmeler oluşturmuştur. Kolayda örnekleme yöntemiyle ulaşılan 301 orta ve üst düzey yöneticiye çevrim içi anket uygulanmış; veriler Yapısal Eşitlik Modellemesi (YEM) ile analiz edilmiştir. Ölçüm modeline ilişkin değerler (CFI=0.999, TLI=0.998, RMSEA<0.08) mükemmel uyum göstermiştir. Bulgular, BVY'nin TZE üzerinde pozitif ve anlamlı bir etkisi olduğunu (β=0.483, p<0.001) ortaya koymuştur. TZE, İP'nı güçlü biçimde etkilemekte (β=0.734, p<0.001), buna karşın BVY'nin İP üzerindeki doğrudan etkisi anlamsız bulunmuştur (β=0.038, p=0.348). Dolaylı etki anlamlı olduğundan (β=0.355, p<0.001), TZE'nin bu ilişkide tam aracılık rolü üstlendiği belirlenmiştir. Ayrıca ÇB'nin, BVY ile TZE arasındaki ilişkiyi zayıflatan bir düzenleyici etkiye sahip olduğu görülmüştür (β=−0.155, p=0.004). Sonuç olarak, BVY İP'nı doğrudan artırmamakta; bununla birlikte esnek tedarik zincirleri aracılığıyla dolaylı biçimde geliştirmektedir.

Anahtar kelimeler: Büyük Veri Yetkinliği, Tedarik Zinciri Esnekliği, Çevresel Belirsizlik, İşletme Performansı, Yapısal Eşitlik Modellemesi
JEL Sınıflaması: M11, M15, L25, O33, C38

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1. Introduction

Digital transformation is defined as a process that aims to improve an asset by creating radical changes in its basic qualities through the combined use of information, informatics, communication, and connection technologies (Vial, 2019). Processing, storing, and transmitting large-scale data at low costs; In addition, thanks to the interpretation ability of advanced software that can make autonomous decisions based on machine learning, digitalization has the potential to transform almost all types of human labor and lifestyles associated with both data and non-routine cognitive processes (Loebbecke & Picot, 2015). In this context, BDC, central to digital transformation, is an indispensable component of digital business strategy for businesses aiming to gain or maintain a competitive advantage in the market (Bharadwaj et al., 2013). Although big data is seen as a source of competitive advantage by many researchers, it is not considered sufficient for companies to create, obtain or invest in big data in terms of competitive advantage, and BDC as an organizational capability that will be created by combining financial, physical, human and organizational resources that can transform big data into insight within the framework of Resource-Based View (RBV) (Gupta & George, 2016). As a knowledge-based dynamic capability, BDC is an important source of insight and value for firms (Lavalle et al., 2011; McAfee et al., 2012; Zheng et al., 2011). It is known that businesses, as for-profit organizations, have a sociotechnical structure (Keskin et al., 2016). BDC has the potential to make invaluable contributions to businesses with sociotechnical systems by providing opportunities for data-driven decision-making based on technology and individual alignment (Akter et al., 2016). Despite this potential, empirical studies investigating the value that BDC brings to businesses are limited (Günther et al., 2017; Mikalef et al., 2019). Studies on big data are mostly focused on its technical features, and studies on how it will strategically lead to a change in organizations have been limited (Mikalef et al., 2020). Much of the information about the business value of big data to date has come from consulting firms, popular press, and case studies that lack theoretical understanding (leading sources), which gives firms a limited perspective on how to approach big data initiatives due to the lack of sufficient empirical evidence (Gupta & George, 2016; Mikalef et al., 2020). Since Resource-Based View (RBV) and related approaches do not focus directly on contextual differences (Kraaijenbrink et al., 2010), theoretical understanding can be broadened by investigating how internal and external conditions play a role between organizational capabilities and competitive advantage (Dubey et al., 2019). For this reason, in the present study, it is proposed to investigate the differences that may occur according to internal and external conditions, such as SCF and EU,

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to understand how the relationship between BDC and BP will follow under different conditions. The sample of the research consists of a total of 301 middle and senior managers working in the information technologies, iron and steel, logistics, manufacturing, machinery production, automotive, plastics, textile, health, energy, construction, tourism, and finance sectors.

2. Literature review

2.1. Big data capability

BDC is defined as a firm's ability to acquire, store, process, and analyze large amounts of data in various forms and deliver information to users that allows organizations to extract value from big data in a timely manner. Big data sources are expressed as a combination of complementary information technology resources related to the use of big data to improve company performance (Kung et al., 2015). When the definitions and studies conceptualizing big data analytics capability are examined, it is seen that big data competence is of a nature that includes organizational resources and talents to include the concept of big data (Gupta & George, 2016). Conceptual and empirical research on BDC as a knowledge-based dynamic capability shows that BDC is a knowledge-based dynamic capability that can be a source of competitive advantage and high-level performance (Kaur & Mehta, 2017; Mikalef et al., 2020; Rialti et al., 2019).The Resource-Based View (RBV) emphasizes that BDC is not just a technical analytical capability but a strategic resource that enhances efficiency, facilitates knowledge sharing, and strengthens innovation capacity across the business (Madhani, 2022; Orero-Blat et al., 2025). It is possible to say that the potential provided by BDC not only stands out in technical areas to extract and process information from data, but also contributes positively to the strategic level of the organization, operational processes, marketing, and other managerial activities (Sheng et al., 2017). According to Shamim et al. (2019), big data capability is the factor that contributes significantly to the efficient use of business resources and the ability of managers to make the right decisions (Shamim et al., 2019). Thanks to the use of big data capability, businesses contribute positively to their performance by achieving higher profits and growth compared to those that do not use this capability (Günther et al., 2017; McAfee et al., 2012).

2.2. Supply chain flexibility

The concept of organizational flexibility is the situation in which organizations gain competencies that can survive in variable environmental conditions (Liao, 2020; Wong et al., 2011). According to Dubey et al. (2020), organizational flexibility is as much an organizational design issue as it is a managerial issue (Dubey et al., 2020). Organizational flexibility is not

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only the managerial skills and competencies that will enable the organization to adapt to the changing environmental conditions of the managers; It also depends on the combination of resources that allow the organization to adapt to different environmental conditions, increasing the control ability of the organization and management, removing hierarchical barriers, cross-functional collaborations, and the presence of multi-purpose teams and equipment. The ability to adapt to variable environmental conditions makes the concept of organizational resilience a critical supply chain performance component. Sirinivasan and Swink (2018) evaluated the concept of flexibility as a concept that should be addressed at the supply chain level and stated that supply chains should be reconfigured to adapt to changes in supply and demand conditions (R. Srinivasan & Swink, 2018) . According to Shekarian and Parast (2021), flexibility-based strategies are the most effective strategies for solving disruptions and disruptions in supply chains (Shekarian & Mellat Parast, 2021). Increased flexibility in supply chains is an increase in capability that enables supply chains to operate more smoothly in a competitive business environment. On the other hand, when the concept of flexibility is defined as "the ability to react to external environmental conditions", this means improving the level of resilience without compromising the level of organizational efficiency. Therefore, SCF not only improves the ability to react to negative influences from the external environment; The ability to change and adapt that comes with flexibility also allows the business to increase its capacity to turn positive changes into opportunities. According to Dynamic Capabilities Theory (DCT), the ability of businesses to achieve sustainable competitive advantage depends on their ability to sense changes in the external environment, seize (seize) new opportunities, and reconfigure existing resource structures (Helfat & Martin, 2015). In this context, supply chain resilience is considered a practical reflection of the dynamic capabilities of the business.

2.3. Environmental uncertainty

Uncertainty refers to an immeasurable risk. Resource dependence theory suggests that environmental uncertainty arises from a lack of control over external resources. In contrast, knowledge-based theory has attributed it to the difficulty of understanding and obtaining external knowledge (Chen & Tian, 2022). EU arises from the inability to access sufficient information in the decision-making process and to predict the future (Lee, 2014). EU can be caused by predictable or unpredictable factors such as customers, suppliers, competitors, markets, wholesalers, employers, and technology, among others. Among these factors, technology, markets, and competitors are among the sources that cause the most environmental uncertainty due to their rapid change and development (Darvishmotevali et al., 2020). In the

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EU environment, environmental factors illustrate to some extent the possibilities of how they affect the success or failure of a business. EU can be summarized as the inability to assign probabilities to the probability of future events, lack of knowledge about cause-and-effect relationships, and the inability to accurately predict the outcomes of a decision (Inman & Green, 2022). Businesses often face environmental uncertainty. The high level of environmental uncertainty in supply chains affects the partnership quality and supply chain performance of organizations (Jangga et al., 2015). In addition, high levels of EU can lead to an increase in various supply chain risks, such as opportunistic behavior between partners (M. Srinivasan et al., 2011).

2.4. Business performance

There are two types of BP that can be used to assess a company's ability to achieve its strategic goals. Financial (profitability, sales growth) and operational (efficiency, quality, and customer satisfaction) are all indicators that can be used to measure BP (Chan, 2003). Modern approaches to performance measurement consider processes that are supported by digital transformation and data analytics to be integral parts of this structure, while Beamon (1999) considered performance measurements along the lines of cost, flexibility, and time(Beamon, 1999). As a result, BDC contributes to the improvement of processes by increasing the quality of operational decision-making; It also makes performance sustainable through the use of supply chain flexibility (Düzcan & Fidan, 2023). Consequently, BDC makes BP a result of combining digitalization with an SCF.

3. Theoretical model and hypotheses development

Big data supports businesses' strategic decision-making processes, increases operational efficiency, and improves customer experience (Hoque et al., 2025). The impact of big data on business performance is of increasing importance in today's business world and can contribute to businesses gaining a competitive advantage and achieving sustainable growth. Businesses using big data gain significant advantages over their competitors such as expanding their business structures, performing R&D and application activities more comprehensively, conducting customer analysis, increasing revenue, etc. Businesses that do not use big data and are caught unprepared act with a non-technological traditional trade approach and therefore lose their competitive advantage compared to businesses that benefit from big data technology. It is seen that most of the enterprises use information management practices in their operations and supply chain to develop highly competitive, information-based products with added value and to increase their market share worldwide by increasing their efficiency and effectiveness, thus gaining advantageous positions in global competition (Wamba et al., 2017).

In this context, the relevant research hypotheses are given below;

H1: There is a significant relationship between BDC and BP.

Flexibility is critical to the long-term survival of an organization (Upton, 1994). In the short term, flexibility affects the firm's competitive stance and can impact its overall profitability. Flexibility becomes particularly important when considering that the entire supply chain consists of a network of procurement, manufacturing, and delivery firms. In this case, many sources of uncertainty need to be addressed (Giannoccaro et al., 2003). Flexibility allows production to be switched between different facilities and suppliers so that management can deal with internal external variability (Kannan, 2005). The emphasis on various dimensions of SCF can be directly linked to overall BP.

H2: There is a significant association between SCF and BP.

H4: SCF has a mediator role in the relationship between BDC and BP.

There are many uncertainties in businesses in terms of faster adaptation and decision-making (Üstündağ & Ungan, 2020). These can be caused by many reasons, including the least affected decisions made inside and outside the enterprise (Topoyan M, 2009). Fluctuations in demand, supplier changes, price fluctuations or unexpected events, etc., are some of them (Stevenson & Spring, 2007). The concept of resilience has been developed to deal with these uncertainties (Chirra & Kumar, 2018). Supply flexibility is defined as the ability of the supply chain to adapt to changing conditions (Mentzer et al., 2001). Supply flexibility increases the ability of the supply chain to cope with the uncertainties and risks it faces, allowing customers to provide continuous, uninterrupted service. Due to increasing competition in global markets and shifts in customer expectations, businesses must ensure and continuously improve supply flexibility (Tang, 2006). Supply flexibility can be achieved through methods such as adjusting stock levels, searching for alternative suppliers, quickly changing production processes, or making logistics processes flexible (Christopher, 2021). Therefore, supply flexibility in supply chain management is critical for the success and sustainability of businesses.

H3: There is a significant relationship between BDC and SCF.

BP is also negatively affected in the event of EU. One of the most important tools that businesses can use to increase their performance in environmental uncertainty situations is the

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adoption of strategic flexibility in the business structure (Grewal & Tansuhaj, 2001). Businesses that adopt strategic flexibility have a better chance of eliminating the threats posed by areas of environmental uncertainty or turning them into opportunities. This competence, which increases the visibility of information in the supply chain, also supports SCF by strengthening the resilience of the business (Zhang et al., 2023). Accordingly, the EU is expected to play a moderating role in this relationship. In this context, the relevant research hypothesis is given below.

H5: EU plays a moderating role in the relationship between BDC and SCF.

As a result of these theoretical foundations, two structural models were developed in the course of the research. In Model 1, the effect of BDC on BP is being tested and the role of SCF as a mediating factor in this relationship will be examined. A key objective of this model is to explain how big data capabilities assist in improving business performance indirectly by increasing agility in supply chain processes, which in turn enhances business performance. This model allows the variable EU to be included as a moderator element in the model. The assumption of the proposed model is that the EU plays a key role in strengthening or weakening the relationship between the BDC and SCF by acting as a factor that influences both parties. Figure 1 illustrates the structure of the relationships between Models 1 and 2 developed within these frameworks in terms of the structural elements.

3. Method

A total of 301 participants worked in a variety of industries throughout Türkiye, including information technology, iron and steel, logistics, manufacturing, machinery production, automotive, plastics, textiles, healthcare, energy, construction, tourism, and finance (Table 1). The target population consisted of organizations that actively utilize digital technologies, particularly big data analytics, within their supply chain operations. In order to reach participants with managerial or executive positions directly involved in supply chain decision-making processes, a non-probability convenience sampling method was employed. In order to collect the data, an e-mail survey and professional networks were used. Structured equation modeling (SEM) with at least 200 observations is recommended by Boomsma (1985). In the current study, there are 301 valid responses, which ensures statistical adequacy. According to Kline (2016) and Hair et al. (2015), the sample size meets the "ten observations per latent variable" rule for SEM applications (Boomsma, 1985; Hair et al., 2014; Kline, 2016).

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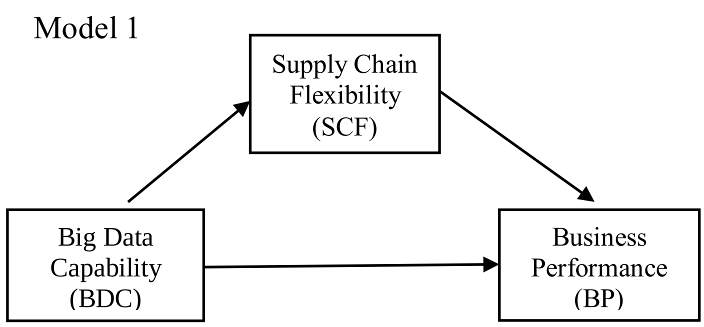
Table 1. Demographic and Professional Characteristics of The Participants

Category		n	%
Gender	Female	84	27.9
	Male	217	72.1
Age	25-44	199	66.1
	45-59	83	27.6
	60-65	19	6.3
Education	Bachelor	175	58.1
	Master	97	32.2
	PhD	29	9.6
Your current length of employment	Less over a year		
	1-4 years	38	12.6
	5-7 years	52	17.3
	8-10 years	60	19.9
	11 + years	53	17.6
Managerial position	Middle	236	78.4
	Senior	65	21.6

3.1. Models and data collection tools

Using SCF as a mediating factor for the effect of BDC on BP, and EU as a moderation factor for the effect of BDC on BP, this study investigates the effects of BDC on BP. In Model 1, SCF is examined as the amplification mechanism that mediates the relationship between BDC and BP, while in Model 2, EU is examined as a moderating mechanism that influences the strength of the relationship between BDC and BP. According to Figure 1, there are a number of conceptual models that have been developed as part of this research framework. Data was collected in this study using a survey technique as a method of collecting information. Participants were asked to complete the online survey form by using the Google Forms platform, which was delivered via e-mail, WhatsApp, and LinkedIn to the participants through a number of digital communication channels. The questionnaire form consists of two parts. In the first part, demographic questions about the gender, age, education level, length of employment, and positions of the participants were included.

Figure 1. Models Utilized in the Research



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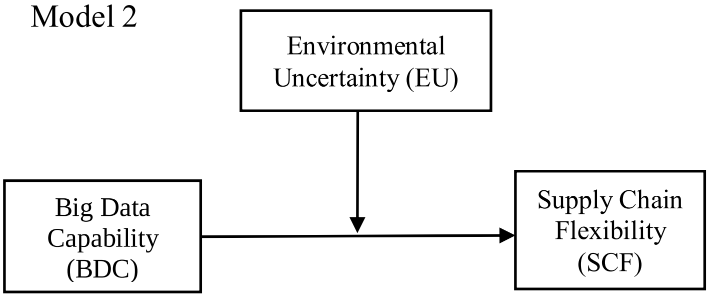
Model 2



In the second part, scale expressions were used to measure the main variables of the research. In this context, the BDC scale was adapted from the five-item structure developed by Meral Çalış Duman (2020). The SCF scale was constructed with five items using expressions developed by Qi, Boyer, and Zhao (2009), Qi and Sheu (2011), Akçi (2012), Qrunfleh and Tarafdar (2014), Swafford, Ghosh and Murthy (2006), and Kurt and Akçacı (2024). The BP scale consists of four items adapted from the work of Chan (2003) and Beamon (1999). The variable EU was included as a moderator and was adapted from four statements in the work of Chen et al. (2014), Kearns and Lederer (2003), and Chen and Zhang (2016) (Table 2).

Table 2. Expressions For Variables

Scale	Items	Source
Big Data Competency (BDC)	Big data analysis is used in decision-making processes. Big data solutions are used in production and supply chain activities. Big data increases the speed of our business processes. Big data applications increase our responsiveness to customer demands. Big data infrastructure is at a level to meet future needs	Meral Çalış Duman (2020)
Supply Chain Flexibility (SCF)	The supply chain adapts quickly to changing market conditions. The supply chain can develop alternative solutions to meet unexpected increases in demand. Operations adapt quickly to environmental changes and uncertainties. In times of crisis, we can use alternative supplier and logistics options. Its processes are crisis-proof and continue to operate steadily.	Qi vd.(2009), Qi ve Sheu (2011), Akçi, Y. (2012), Qrunfleh ve Tarafdar (2014), Swafford, Ghosh ve Murthy (2006). Kurt, F. B., & Akçacı T. (2024).
Business Performance (BP	Customer satisfaction has increased in recent years. Financial performance is above the industry average. Operational efficiency (cost, quality, delivery) has increased. There was an increase in market share.	Chan (2003); Beamon (1999)
Environmental Uncertainty (EU) *(Moderator)*	In our industry, there is intense competition in terms of quality or price of products or services. *(competition)* In our industry, customer demands and expectations change unpredictably. *(customer demand / variety).* Legal/political regulations create uncertainty. Economic and technological conditions fluctuate rapidly and unpredictably. *(economy + technology).*	*Chen vd. (2014), Kearns ve Lederer (2003),* Chen ve Zhang (2016).

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The expressions of the scales were measured with a 5-point Likert-type scale (1=Strongly Disagree, 5=Strongly Agree). The Turkish form of the scales has been revised in line with expert opinions regarding language validity and content suitability. To establish the scales on a strong conceptual and empirical foundation, valid and reliable measurement tools widely used in the relevant literature were employed. Ethics Committee Permission, dated 27 October 2025 and numbered 04-60660/2025-10, was obtained from the Istanbul Rumeli University Ethics Committee Presidency for the data collection process. The survey was conducted between November 1, 2025, and November 15, 2025. Participants were informed about the purpose of the research, confidentiality principles, and the principles of voluntary participation; only the responses of participants who consented were included in the analysis. Incomplete or inconsistently filled questionnaires are excluded from the evaluation (Akçi, 2012; Beamon, 1999; Çalış Duman, 2020; Chan, 2003; X. Chen & Zhang, 2016; Y. Chen et al., 2014; Kearns & Lederer, 2003; Kurt & Akçaci, 2024; Qi et al., 2009, 2011; Qrunfleh & Tarafdar, 2014; Swafford et al., 2006).

4. Findings and Discussion

Cronbach's α coefficients were calculated to evaluate the internal consistency of the variables used in Model 1 and Model 2. According to the results presented in Table 3, all scales were found to be highly reliable. Cronbach's α value was 0.930 for the BDC scale, 0.875 for the BP scale, 0.837 for the SCF scale, and 0.891 for the EU scale. Taking into account the 0.70 threshold proposed by Nunnally and Bernstein (1994), it is seen that all scales have values well above the acceptable limit. These findings suggest that the measurements used in the research are consistent and reliable (Nunnally & Bernstein, 1994).

Table 3. Scale's Reliability Statistics

	Mean	SD	Cronbach's α
BDC	4.70	0.606	0.930
BP	4.71	0.531	0.875
SCF	4.75	0.407	0.837
EU	4.69	0.498	0.891

4.1. Results of the measurement model

The variables' measurement models were evaluated using AMOS 22.0 software with the Maximum Likelihood Estimation (MLE) method. Initially, individual measurement models for each latent variable were tested, and the fit indices are summarized in Table 4. Goodness of fit

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values between 1.29 and 3.75, RMSEA values under .08, and CFI values above .97 indicate that all models meet the recommended threshold (Kline, 2016).

Table 4. Model Outcomes

	CMIN	DF	CMIN/DF	RMSEA	CFI	TLI	AVE	CR
BDC	6.463	5	1.293	.031	.999	.998	.73	.93
BP	2.341	1	2.341	.067	.997	.980	.51	.80
SCF	8.996	4	2.249	.065	.991	.978	.57	.83
EU	3.757	1	3.757	.086	.996	.977	.68	.89

Consequently, all factors exhibit discriminant validity since their AVE estimates are greater than their squared correlations (see Table 5).

As a way of evaluating convergence validity, we examined standardized factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Hair et al. (2014) recommend CR values of over .70 and AVE values of over .50 for quantitative research. Table 4 shows that factor loadings all exceeded .70, CR values ranging from .80 to .93, and AVEs ranging from .51 to .73. As a result, CR exceeded AVE for all constructs, indicating that indicators shared variance and internal consistency (Hair et al., 2014).

Table 5. Evaluation of the Fornell-Larcker Criterion for verifying Discriminant Validity

Model 1	**(1)**	**(2)**	**(3)**
1.SCF	.755		
2.BDC	$.629^{***}$	.855	
3.BP	$.617^{***}$	$.527^{***}$	.714
Model 2	**(1)**	**(2)**	**(3)**
1.BDC	.719		
2.SFC	$.640^{***}$	.855	
3.EU	$.701^{***}$	$.541^{***}$	.829

***Significance at 0.01 (two-tailed).

According to the results of Table 4 the χ^2/df ratios in the range of 1.29–3.75 and RMSEA values below .08 prove that the model is well fitted. CFI (.996–.999) and TLI (.977–.998) values are also above .97, indicating that the model is perfectly compatible (Hu & Bentler, 1999). In terms of convergent validity, CR values of all structures are between .80 and .93 and above .70; AVE values are also in the .51–.73 range and exceed the .50 threshold. These results suggest that each variable shares sufficient common variance with its indicators, ensuring internal consistency (Hair et al., 2014). In addition, the CR > AVE condition is met in all structures.

The validity of the discriminant was confirmed by the Fornell-Larcker criterion. As seen in Tables 5, the square root of the AVE, located on the diagonal of each variable, is greater than its correlations with other variables. This shows that each structure is distinguishable from the

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others and that the measurement model maintains its multidimensionality. As a result, the measurement model meets all the validity and reliability criteria, the variables are statistically distinguishable from each other, and it is suitable for the transition to the structural model.

4.2. Hypothesis testing

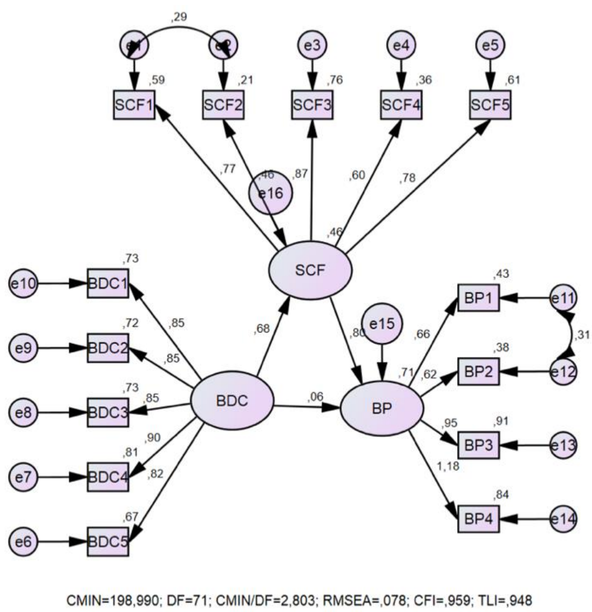
Within the scope of Model 1, the Structural Equation Model (Figure 2) was created to test the causal relationships between the variables BDC, BP, and SCF. The overall goodness-of-fit statistics of Model 1 show that the data have a good level of fit to the model. In particular, the ratio $\chi^2/sd = 2.803$ is below the recommended limit of 3; RMSEA =0.078 is acceptable. Additionally, the values of CFI = 0.959 and TLI = 0.948 indicate that the model exhibits good fit.

Table 6. Path Coefficients for the Structural Equation Model (Model 1)

Hypotheses	Path	Standardized (β) Coefficient	t-value (C.R.)	p-value	Result
H1	BDC → SCF	0.483	10.745	p < 0.001	Supported
H2	BDC → BP	0.038	0.938	0.348	Not supported
H3	SCF → BP	0.734	8.935	p < 0.001	Supported

Indirect Effect		Bootstrap %95 CI	p-value	Result
H4	BDC → SCF → BP	0.355 [0.19, 0.53]	p < 0.001	Supported (Mediating Role)

Figure 2. Structural Equation Model (Model 1)



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The pathway coefficients in Table 6 show that BDC has a significant and positive effect on SCF ($\beta = 0.483$, $p < 0.001$). However, the direct effect of BDC on BP was not statistically significant ($\beta = 0.038$, $p = 0.348$). The indirect impact of BDC on BP is revealed through SCF. In other words, data-driven decision-making processes and digital infrastructure investments indirectly strengthen business performance by encouraging the formation of flexible and compliant supply chains, rather than directly increasing performance. The effect of the SCF variable on BP was strong, positive, and significant ($\beta = 0.734$, $p < .001$). This finding suggests that businesses with SCF can improve BP.

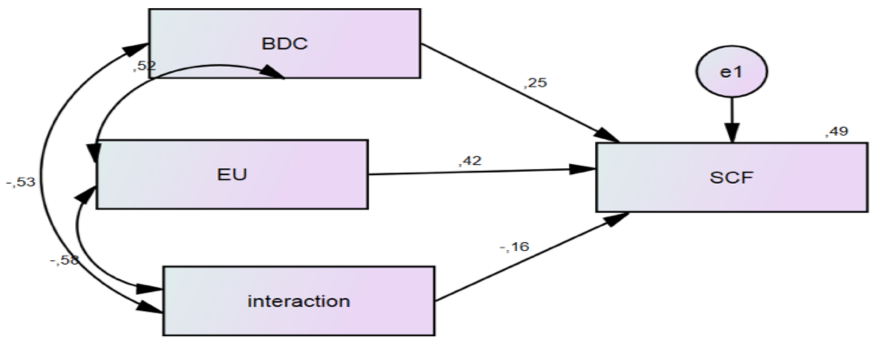
According to the Bootstrap analysis, the indirect effect of BDC on BP was found to be significant through SCF ($\beta = 0.355$, [0.19 – 0.53], $p < .001$). This result shows that SCF plays a mediating variable role in the relationship between BDC and BP. Therefore, BDC does not affect BP directly, but indirectly by enabling the formation of SCF.

According to the results of Model 2, BDC significantly and positively affects SCF ($\beta = 0.254$, $p < .001$). Likewise, the EU variable has a significant effect on SCF ($\beta = 0.422$, $p < .001$). However, the BDC × EU interaction term was found to be significant and negative ($\beta = –0.155$, $p = .004$). This finding suggests that as environmental uncertainty increases, the positive impact of BDC on SCF weakens. Therefore, the variable EU plays a moderating role in the relationship between BDC and SCF (Table 7).

Table 7. Results for the Moderation Model (Model 2)

Dependent Variable: SCF	Estimate	S.E.	C.R.	p	Standardized β
BDC → SCF	0.517	0.104	4.990	***	0.254
EU → SCF	0.859	0.108	7.973	***	0.422
BDC*EU → SCF	-0.109	0.037	-2.911	0.004	-0.155

Figure 3. The moderating effect of the EU



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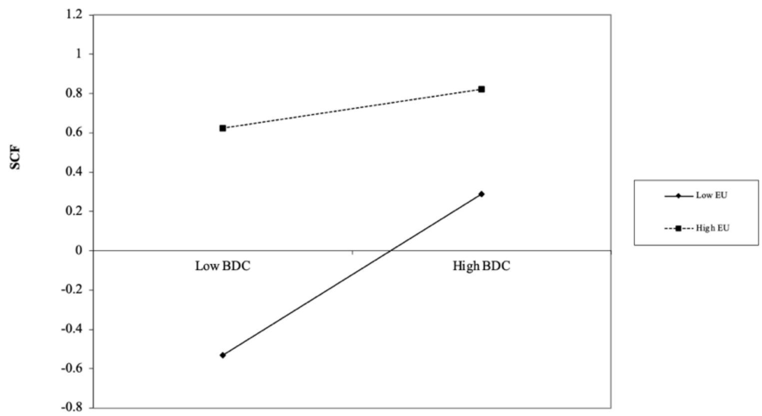
According to the results of simple slope analysis, when the EU level was low (–1 SD), the effect of BDC on SCF was significant and positive (β = 0.409, t = 3.137, p = 0.002). On the other hand, when the level of environmental uncertainty is high (+1 SD), this relationship becomes insignificant (β = 0.099, t = 0.626, p = 0.532). As seen in Figure 4 and Table 8, the effect of BDC on SCF is stronger under conditions of low environmental uncertainty; however, this effect weakens as uncertainty increases. This finding suggests that environmental uncertainty negatively regulates the relationship between BDC and SCF (negative moderation).

Table 8. Simple slope test results for the Moderation effect of EU

Moderator Level	Gradient of Slope (β)	t-value	p-value
Low EU (–1 SD)	0.409	3.137	0.002
High EU (+1 SD)	0.099	0.626	0.532

Figure 4. Moderating Effect of EU on the relationship between BDC and SCF



As a result of the findings obtained in this study, it is understood that the effect of BDC on BP is not direct, but indirectly through SCF. The findings are largely in agreement with the pioneering empirical research conducted by Mikalef et al. (2020) and Fosso et al. (2018). Mikalef et al. (2020), in their structural equation model analysis conducted with 202 senior executives in Norway, state that BDC does not affect business performance directly, but indirectly through dynamic talents, and that this effect occurs especially through restructuring in marketing and technological capabilities. In the current study, the direct effect of BDC on business performance was not statistically significant (β = 0.038, p = 0.348), while the indirect effect through SCF was found to be significant (β = 0.355, p < 0.001). This result coincides with the finding of Mikalef et al. (2020) that "technological investment alone is not enough to create a competitive advantage, the real value lies in the capacity for organizational

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restructuring and learning". Similarly, in another study, Fasso et al. (2018) stated that BDC's contribution to business performance is strengthened by the interaction of organizational learning, data-based culture and human capital elements (Fosso Wamba et al., 2018; Mikalef et al., 2020).

Environmental uncertainty (EU) has been observed to debilitatingly moderate the relationship between Big Data Competence (BDC) and Supply Chain Resilience (SCF). Mikalef et al. (2020) consider environmental uncertainty as an exogenous factor that conditions the impact of big data on performance outcomes. They argue that the value creation potential of Big Data Analytics Capability (BDAC) depends on the level of compliance within the organization. Fosso et al. (2018) argues that the technological, human, and managerial dimensions of BDC support the perception-capture-restructuring cycles of businesses; thus, it has shown that it increases operational flexibility and competitive performance. This mechanism serves a similar function to the mediating role of SCF described in our study. Rather than directly increasing production or sales, BDC contributes to business performance through data-driven agility, rapid adaptation to demand fluctuations, and risk mitigation. Zehir (2022), in their research based on the Turkish sample, revealed that BDAC affects firm performance in different ways depending on business size and digital maturity level. The findings from this study coincide with the general trends in the literature (Dubey et al., 2020; Fosso Wamba et al., 2018; Mikalef et al., 2020; Zehir, 2022)

5. Results and Recommendations

The findings of this study highlight the pivotal role of supply chain flexibility in transforming big data capabilities into tangible business performance outcomes. The analysis revealed that big data capability (BDC) has a strong and significant impact on supply chain flexibility (SCF) ($\beta = 0.483$, $p < .001$), indicating that data-driven organizations are better able to adapt to dynamic market conditions, manage uncertainty, and reconfigure their operational processes effectively. However, the direct effect of BDC on business performance (BP) was found to be statistically insignificant ($\beta = 0.038$, $p = .348$), suggesting that technological and analytical investments alone are insufficient to improve firm performance without the support of adaptive operational mechanisms. On the other hand, SCF demonstrated a robust and significant influence on BP ($\beta = 0.734$, $p < .001$), emphasizing that flexible supply chains are a crucial determinant of efficiency, customer satisfaction, and competitive advantage. Furthermore, the mediation analysis confirmed that SCF fully mediates the relationship between BDC and BP ($\beta = 0.355$, $p < .001$), implying that the performance benefits of big data are realized indirectly through enhanced supply chain responsiveness and adaptability. These results collectively suggest that big data capability, while essential, becomes strategically valuable only when integrated into flexible supply chain structures. In line with the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT), the study concludes that organizations achieve sustainable performance improvements not merely by collecting and analyzing data but by transforming these analytical competencies into dynamic, reconfigurable, and resilient operational processes.

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