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The Role of Supply Chain Transparency in the Relation between Supply Chain Analytics Capabilities and Firm Performance

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ABSTRACT

Ever-increasing data change the business environment with a great acceleration. This unavoidable data growth brings uncertainties and causes heavy pressure on firms. In this context, supply chain analytics have much more attention in order to manage data in the field of supply chain management. Despite the growing interest in analytics capabilities, the studies are in its early stages. The current study investigated the role of supply chain transparency in the relation between supply chain analytics capabilities and firm performance. The data was gathered via survey from 100 participants from different companies and the PLS-SEM was used in order to investigate theoretical framework. The results indicate that enhanced supply chain analytic capabilities have positive impacts on the firm performance and the supply chain transparency positively moderates this relationship.

Keywords: *analytic capability, firm performance, supply chain transparency*

1. INTRODUCTION

For companies, the ability to take advantage from big data has become critical for the keeping up with ongoing globalization. Companies which considering that data as a strategic asset will gain competitive advantage (Davenport & Harris, 2007; McAfee & Brynjolfsson, 2012). Within the digitalization of businesses, data started to flow to firms from multiple channels at the same time. Many sources, such as the Internet of things (IoT), sensors, cloud-based systems, smart phones, social media, log files and day-to-day transactional reports, have become a main source of data. This massive amount of data also known as big data, contains structured and unstructured, real-time, and almost real-time data which can be used for better decision making (Jeble, Kumari, & Patil, 2018; Raman *et al.*, 2018; Sipahi & Timor, 2010). By integrating big data analytics into supply chain management systems, supply chain analytics capabilities can be improved.

Supply Chain Analytics offers companies to now-how when, why, and how often their customers will buy specific products. It also expresses the beginning of an era that revolutionized the business world in almost every industry. As the supply chain becomes more complex, the demand for effective information technology solutions to manage the flow of goods and information increases (Huddiniah, ER, & Journal, 2019). Big data also guides the companies to manage their operations and services much more efficiently (Dubey *et al.*, 2019; Frederico, Kumar, Garza-Reyes, Kumar, & Agrawal, 2023; Khan, Piprani, & Yu, 2023). On the other hand, transparency is an increasingly important capability for companies. Supply chain transparency (SCT) can be defined as the ability to track movement of products from the manufacturer to the end-user. The main purpose is to disclose detailed and accurate information about operations and products to all stakeholders and customers (Montecchi, Plangger, & West, 2021; Shafiq, Ahmed, & Mahmoodi, 2020; Sodhi & Tang, 2019). Transparency is one of the most important customers' demands as is regulatory requirements. Supply chain analytics capability can impact on firm performance in various ways.

The relationship between firm performance and its capability in supply chain analytics is intricate and diverse. Numerous elements contribute to the dynamics of this correlation, and it may differ depending on the industry, organizational environment, and the analytics capabilities under consideration. Recent studies suggest a positive relationship between supply chain analytic capabilities and firm performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Wamba, Ngai, & Riggins, 2017). The analytics capabilities approach has become widely embraced as a framework for elucidating the performance differences among competing firms (Brusset & Teller, 2017). Kim *et al.* (2012) initially introduced the concept of managing big data analytics (BDA) capabilities, a notion later expanded upon by Akter *et al.* in 2016. This framework was subsequently refined for application within the supply chain context, resulting in the development of supply chain analytics capabilities, as elucidated by Fosso Wamba and Akter in 2019.Therefore, there is a lack of studies that how analytics capabilities can improve firm performance (Akter *et al.*, 2016; Bahrami & Shokouhyar, 2022; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Zhu, Song, & Hazen, 2018).

Yudhistyra and co-workers, in review article (2020) where they investigated the implementation of big data, mentioned research gaps related to big data and emphasized the necessity of conducting studies with real data. In this study, all aspects that could impact the supply chain were examined, and the importance of analytical capabilities with real data was emphasized. Additionally, the effects of transparency on the entire supply chain process were also investigated (Yudhistyra, Risal, Raungratanaamporn, Ratanavaraha, & Journal, 2020).

This research serves to connect theoretical principles with real-world implementations. Gaining insights into the influence of analytical capabilities on the field of supply chain management can offer practical and actionable guidance for businesses. Herein, this study determines the role of supply chain transparency in the relation between analytics capabilities and firm performance. The study integrates two crucial concepts in supply chain management – analytics capabilities and transparency. It explores how these elements interact and jointly influence firm performance. This insight is valuable for business leaders aiming to optimize their supply chain strategies. Findings were based on a qualitative analysis of data gathered from supply chain managers and mid-level managers via online 5 point-Likert survey (1=strongly disagree to 5=strongly agree). Structural equation modeling was performed with a sample of 100 survey participants from different companies.

2. CONCEPTUAL FRAMEWORK

2.1 Supply Chain Analytics Capability

Recent studies have shown that three main dimensions reflect supply chain analytics capabilities in the literature. These dimensions referred as follows: Supply chain analytics management capability, supply chain analytics technology capability, and supply chain analytics talent capability (Akter *et al.*, 2016; Fosso Wamba & Akter, 2019; Wamba, Gunasekaran, *et al.*, 2017). Wamba and co-workers determined the big data analytics as a higher-order and multidimensional structure, and it has several subdimensions (planning, investment, coordination, control, compatibility, modularity, business knowledge, and relational knowledge were used in this study) (Fosso Wamba & Akter, 2019).

The research model includes a reflective-reflective-formative third-order exogenous construct which supply chains analytic capabilities as a third-order, hierarchical model demonstrated in three second-order constructs – Supply chain management capability, technology capability and talent capability – and eight first-order constructs: Supply chain planning, investment, coordination, control, compatibility, modularity, business knowledge and relational knowledge (see **Figure 1**). Current study also suggest that supply chain analytics capabilities have positive impact on firm performance (Kim, Shin, & Kwon, 2012; Wamba, Ngai, *et al.*, 2017).

2.1.1 Supply Chain Analytics Management Capability

Supply chain management covers a broad process from the production of raw materials required by the manufacturer to the consumer as a product. Supply chain management capabilities have four stages these were termed as SC planning, SC investment, SC coordination, and SC control (Akter *et al.*, 2016). Proper planning activity plays vital role for achieve strategic goals, also refers to scheduling, finance, distribution (Kusrini, Caneca, Helia, & Miranda, 2019; Zhou, Benton Jr, Schilling, & Milligan, 2011). Supply chain investment decisions are critical to companies within the global volatility. Firms must invest agile, resilient, sustainable, and intelligent operations. Supply chain control process ensures proper use of resources, including items such as human resources, budgets, etc (Akter *et al.*, 2016).

2.1.2 Supply Chain Analytics Technology Capability

Supply chain analytics technology capability refers to flexibility of supply chain information technology (IT) infrastructure. IT infrastructure and personnel should be able to quickly adapt to uncertain business environments and rapid changes in customer demand. Supply chain analytics technology capabilities have two stages, followed as SC compatibility and SC modularity (Akter *et al.*, 2016; Fosso Wamba & Akter, 2019; Kim *et al.*, 2012; Wamba, Gunasekaran, *et al.*, 2017). Supply chain compatibility enables to common experiences and common strategies which are shared by supply chain stakeholders (Rajaguru & Matanda, 2019). Supply chain modularity is another significant feature for companies to meet the customer rapidly changing demands. When it comes to technology management, modularity in IT provides flexible platforms that are rebuilt according to need (Akter *et al.*, 2016; Kim *et al.*, 2012).

2.1.3 Supply Chain Analytics Talent Capability

Supply chain talent capability refers to technical skills, knowledge about data analysis, operational - managerial systems and networking (Akter *et al.*, 2016; Constantiou & Kallinikos, 2015). In this study, talent capabilities have two stages, were termed as SC Business Knowledge and SC

Relational Knowledge. SC business knowledge refers to recognize the requirements of business environment and SC relational knowledge refers to communication with rest of the business professionals (Akter *et al.*, 2016; Fosso Wamba & Akter, 2019; Kim *et al.*, 2012).

2.2 Supply Chain Transparency

Supply chain transparency can describe as sharing information regarding current situation of orders, products, production plans and forecasts with all stakeholders including customers (Akkermans, Bogerd, & van Doremalen, 2004; Bai & Sarkis, 2020; Centobelli, Cerchione, Vecchio, Oropallo, & Secundo, 2021). Supply chain transparency enables rapid response to change by companies to act and reshape demand. In addition to sharing information in supply chain processes, customers have demanded accurate and real-time information about the process of the purchased product, as well as information on commercial practices, environmental obligations, compliance rules and regulations (Mol, 2015).

2.3 Firm Performance

Firm performance is the ability of a firm to meet its financial and strategic objectives compared to its competitors (Cao & Zhang, 2011). Denison and co-workers defines the firm performance as the development of firms in terms of quality and quantity in their organizational activities and, in parallel with these developments, the positive effects of direct or indirect financial effects on firms (Denison & Mishra, 1995). There are various measures in the literature that can be used to determine the firm performance. It has been studied using different approaches. One of the most common measures of firm performance is financial performance, it can be measured using different metrics, such as return on investment, return on assets. Besides, non-financial performance also studied with various metrics such as customer satisfaction, employee engagement, and social responsibility (Ahmad & Zabri, 2016; Fullerton & Wempe, 2009). The other approach is resource-based view suggests that a company's performance is influenced by its resources and capabilities. Such resources and capabilities include technology, company reputation, and highly skilled employees(Barney, 1995; Peng Wong & Yew Wong, 2011). Last approach is dynamic capabilities, it refers to firm's ability to adapt in its business environment to achieve superior performance (Protogerou, Caloghirou, & Lioukas, 2011). In this study firm performance was measured by sales growth, profit margin on sales, return on investment, operating revenue and market share (Cao & Zhang, 2011).

3. HYPOTHESIS DEVELOPMENT

3.1 The Relationship between Supply Chain Analytics Capability and Firm Performance

Prior studies investigated a positive relationship between analytics capability and firm performance (Akter *et al.*, 2016; Fosso Wamba & Akter, 2019; Fosso Wamba *et al.*, 2015; Fosso Wamba, Queiroz, & Trinchera, 2020; Kim *et al.*, 2012). So, supply chain analytics capabilities are widely known to play an important role increasing firm performance. When a firm invests in and develops a supply chain analytics capability, it gains the ability to extract valuable insights from the vast amounts of data generated along the supply chain. Today, vast amounts of data are being generated at any given moment in almost every industry. By leveraging analytics, firms can identify their bottlenecks and can adapt their strategies to market changes. This will result in heightened levels of customer satisfaction and enhanced profitability. So, following hypothesis was suggested:

Hyphothesis 1: *There is a positive relationship between supply chain analytics capability and firm performance.*

3.2 The Moderate Effect of Supply Chain Transparency between Supply Chain Analytics Capability and Firm Performance

Supply chain transparency can enhance collaboration and trust among supply chain partners, which it facilitates effectiveness of supply chain analytics and improve firm performance. In other words, firms have high level of analytics capabilities and shares information transparently with its partners and stakeholders, it is expected that positive impact on its performance (Balakrishnan & Ramanathan, 2021; Bastian & Zentes, 2013; Dubey *et al.*, 2020; Ning, Li, Xu, & Yang, 2023). Bastian and co-workers addresses the use of supply chain transparency and related data analytics techniques can enhance sustainability and different dimension of supply chain performance (Bastian & Zentes, 2013).

Transparency ensures that the information shared for supply chain analytics is accurate, reliable, and comprehensive. This, in turn, strengthens the companies for data-driven decision-making. This situation determines the impact of analytical capabilities on firm performance because access to accurate, reliable, and comprehensive data enables more effective analyses and the implementation of information-focused strategies. Analytical capabilities supported by accurate data allow the firm to make better-informed decisions and optimize its processes, ultimately enhancing overall firm performance. So following hypothesis was suggested:

Hypothesis 2: *Supply chain transparency positively moderates the relationship between supply chain analytics and firm performance.*

4. METHODOLOGY

All constructs utilized in the study were based on existing literature and adapted to suit the specific context of the research. Findings were based on a qualitative analysis of data via online 5 point-Likert survey (1=strongly disagree to 5=strongly agree). Research data was collected through a logistics firm operating in Turkey. The firm's customers operating in the chemical and FMCG sectors were contacted and a survey was sent to the supply chain managers and professionals in these customer firms. Since the respondents were contacted one-on-one, feedback was received from all the distributed surveys. After removing a small number of invalid surveys from the data set, 100 valid survey forms were obtained. Structural equation modeling was performed with a sample of 100 survey participants from different companies. In the scope of the study, all survey questions were taken from existing literature and translated into Turkish to be asked to professionals. The representative sample selection included large-scale supply chains from different sectors. To measure Supply Chain Analytics Capability, Supply Chain Technology Capability, Supply Chain Analytics Talent Capability, items were adapted from Fosso Wamba & Akter (2019). Supply Chain Transparency measure was adapted from Zhu *et al*. (2018). Firm performance was measured with a 13-item measure (Akgün *et al.*, 2007; Ellinger *et al.*, 2002).

5. ANALYSIS AND RESULT

The data of the study was analyzed by following partial least squares structural equation modeling (PLS-SEM). PLS-SEM can explore multiple relationships at the same time, and it is a preferred method especially in complex models. In the analysis of this research, PLS-SEM method was applied as it is successful in complex models, can perform with smaller samples and does not seek normality condition. The research model was tested using SmartPLS v. 4.0.8.3. software by following a two-step approach. In the first step, the measurement model was tested, and the reliability and validity of the model were evaluated. Then, the hypothesis of the research were examined with the structural model (Hair, Hult, Ringle, & Sarstedt, 2013).

5.1 Measurement Model

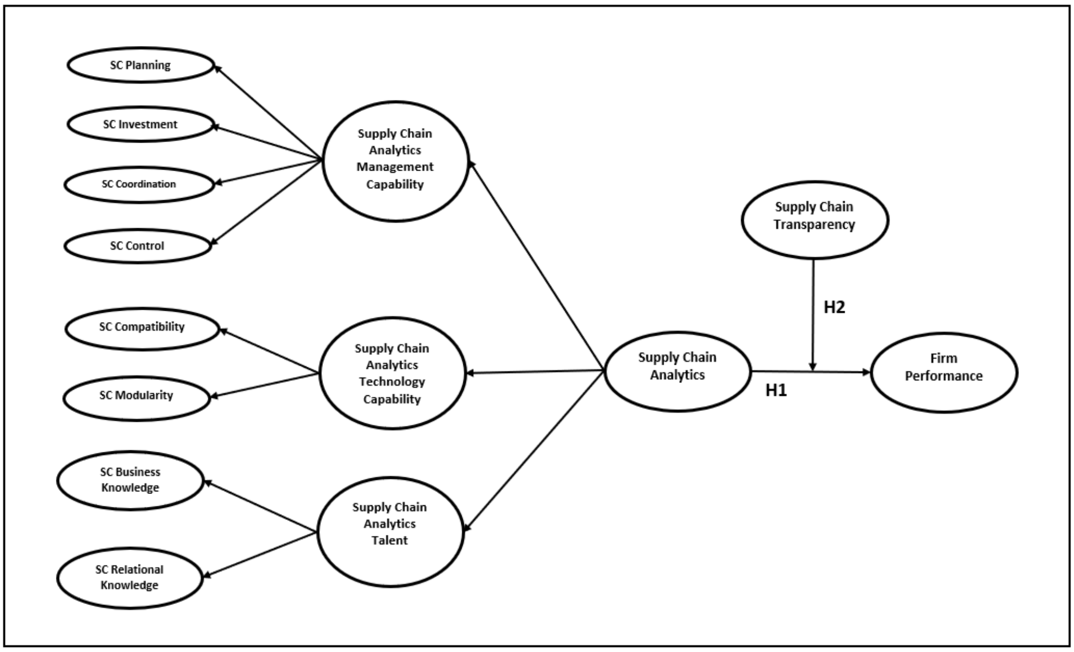

Figure 1 Research model

The research model includes a reflective-reflective-formative third-order exogenous construct. So to estimate the parameters, the repeated indicator approach was used (Becker, Klein, & Wetzels, 2012). Firstly, the validity and reliability of the first-order reflective constructs were evaluated. Afterwards, reliability and validity of second-order reflective constructs were examined. Finally, the validity and significance of the relationship of the third-order formative construct with the second-order constructs was tested.

Factor loadings, Composite Reliability (CR) values and Average Variance Extracted (AVE) values for first-order structures are given in **Table 1**. According to (Hair *et al.*, 2013), factor loadings should be above 0.70. Almost all items in the model have a loading above the 0.70. As an exception, SCPL3 (0.507), SCRK42 (0.547) and FP60 (0.576) have loading below 0.70, but they were not excluded from the model because they were still greater than the critical value of 0.40 and their removal does not increase the reliability or validity of the model (Hair *et al.*, 2013). All constructs in the model have CR values above the threshold value of 0.70. With these results, the reliability of first-order constructs was confirmed.

Table 1 Reliability and validity of first-order constructs

First-Order Constructs	Items	Loadings	CR	AVE
Supply Chain Planning			0.841	0.653
	SCPL1	0.889		
	SCPL2	0.954		
	SCPL3	0.507		
Supply Chain Investment Decision Making			0.864	0.763
	SCID6	0.756		
	SCID8	0.977		

Table 1 Reliability and validity of first-order constructs (Con't)

First-Order Constructs	Items	Loadings	CR	AVE
Supply Chain Coordination			0.954	0.911
	SCCO10	0.974		
	SCCO11	0.935		
Supply Chain Control			0.882	0.714
	SCCT13	0.789		
	SCCT14	0.909		
	SCCT15	0.832		
Supply Chain Compatibility			0.808	0.677
	SCCM21	0.835		
	SCCM24	0.811		
Supply Chain Modularity			0.837	0.633
	SCMD25	0.855		
	SCMD27	0.720		
	SCMD28	0.805		
Supply Chain Business Knowledge			0.926	0.807
	SCBK37	0.905		
	SCBK38	0.861		
	SCBK39	0.928		
Supply Chain Relational Knowledge			0.778	0.549
	SCRK41	0.917		
	SCRK42	0.547		
	SCRK43	0.711		
Supply Chain Transparency			0.958	0.850
	SCT45	0.931		
	SCT48	0.884		
	SCT49	0.919		
	SCT52	0.951		
Firm Performance			0.892	0.547
	FP58	0.813		
	FP59	0.703		
	FP60	0.576		
	FP61	0.601		
	FP62	0.817		
	FP63	0.785		
	FP64	0.835		

Note: CR = composite reliability, AVE = average variance extracted

For a construct to have convergent validity, its AVE value should be above 0.50 (Hair *et. al*., 2017). As shown in **Table 1**, all first-order constructs in the model have AVE values above 0.50, confirming the convergent validity. Two different methods were used to test the discriminant validity of the first-order constructs. First, the constructs were examined according to the Fornell-Larcker approach (Fornell & Larcker, 1981). The square roots of the AVE values for all constructs are greater than their highest correlation with any other construct (**Table 2**). Another method used to test discriminant validity is Heterotrait–Monotrait Ratio (HTMT). According to this method, all HTMT correlation values should be below 0.90 in order to ensure discriminant validity (Henseler, Ringle, & Sarstedt, 2015). As shown in **Table 3**, all values remained below 0.90 and the model met this criterion. The results of these two tests confirm that the model has discriminant validity.

Table 2 Discriminant validity: Fornell-Larcker Criterion

	FP	SCBK	SCCM	SCCO	SCCT	SCID	SCMD	SCPL	SCRK	SCT
FP	**0.740**									
SCBK	-0.192	**0.899**								
SCCM	0.279	0.369	**0.823**							

Table 2 Discriminant validity: Fornell-Larcker Criterion (Con't)

	FP	SCBK	SCCM	SCCO	SCCT	SCID	SCMD	SCPL	SCRK	SCT
SCCO	0.031	0.687	0.297	**0.955**						
SCCT	0.527	0.267	0.309	0.426	**0.845**					
SCID	0.344	0.420	0.356	0.462	0.585	**0.874**				
SCMD	0.403	0.213	0.339	0.096	0.397	0.239	**0.795**			
SCPL	0.449	0.106	0.208	0.220	0.580	0.502	0.538	**0.808**		
SCRK	0.449	0.133	0.279	0.103	0.527	0.199	0.671	0.442	**0.741**	
SCT	0.362	0.037	0.538	0.199	0.325	0.201	0.346	0.196	0.350	**0.922**

Note: Values in diagonal show square-root of the AVE

Table 3 Discriminant validity: Heterotrait–Monotrait Ratio (HTMT)

	FP	SCBK	SCCM	SCCO	SCCT	SCID	SCMD	SCPL	SCRK	SCT
FP										
SCBK	0.211									
SCCM	0.450	0.547								
SCCO	0.091	0.792	0.430							
SCCT	0.583	0.325	0.439	0.458						
SCID	0.403	0.617	0.439	0.646	0.725					
SCMD	0.515	0.262	0.598	0.117	0.546	0.379				
SCPL	0.494	0.188	0.426	0.256	0.799	0.678	0.744			
SCRK	0.507	0.318	0.638	0.278	0.701	0.345	0.827	0.553		
SCT	0.387	0.057	0.742	0.178	0.324	0.257	0.425	0.240	0.489	

After the reliability and validity of the first-order constructs were verified, second-order reflective constructs (SCA Management Capability, SCA Technology Capability and SCA Talent Capability) were created according to the repeated indicator method. **Table** 4 shows the loadings and significance levels of the second order constructs. All loadings of the second-order constructs were found to be significant at the $p < 0.001$ level. In addition, the CR values of the second-order constructs were found above 0.70 and the AVE values above 0.50. After the creation and confirming the validity of the second-order constructs, the formative third-order construct was created.

Table 4 Validity of second-order constructs

Second-Order Constructs	First-Order Constructs	Loadings	T Stat.	P values	CR	AVE
SCA Management Capability					0,860	0,608
	SCPL	0.768	15.634	0.000		
	SCID	0.824	26.337	0.000		
	SCCO	0.649	7.032	0.000		
	SCCT	0.862	27.405	0.000		
SCA Technology Capability					0,806	0,677
	SCCM	0.733	12.119	0.000		
	SCMD	0.904	46.870	0.000		
SCA Talent Capability					0,779	0,642
	SCBK	0.890	31.107	0.000		
	SCRK	0.701	7.609	0.000		

Supply Chain Analytics is the third-order construct of the model based on three second-order construct which is mentioned above. In order to assess the construct validity for formative third-order construct, Variance Inflation Factor (VIF), weights and also significance level of weights were examined (Hair *et al.*, 2013). All the VIF values were below the threshold of 5, so there is no multi-collinearity problem with the construct. The weights of the construct are given in **Table 5**. All the weights were found significant, confirming construct validity. This means the second-order constructs are truly contribute to the third-order construct. With the evaluation of third-order construct, the model is reliable and valid for hypothesis testing.

Table 5 Third-order construct validity

	β	T statistics	P values	VIF
Supply Chain Analytics (R^2= .99)				
SCA Management Capability	0.596	12.671	0.000	1.603
SCA Technology Capability	0.292	7.301	0.000	1.466
SCA Talent Capability	0.302	4.211	0.040	1.708

5.2 Structural Model

Bootstrapping method was performed with 5000 subsamples to test research hypothesis. **Table 6** demonstrates the test results including path coefficients, t statistics and p values. The R^2 value for firm performance was found 0.380. The model explains 38% of the variation in firm performance. The hypothesis test results indicate that both hypotheses were significant. There is a positive relationship between supply chain analytics and firm performance (β= 0.349, p= 0.001), supporting H1.

Finally, the moderation effect of supply chain transparency in the relationship between supply chain analytics and firm performance was evaluated. It was found that there is a significant and positive moderation effect (β= 0.433, p< 0.001), thereby confirming H2. As shown in **Figure 2**, high level of supply chain transparency strengthens the relationship between supply chain analytics and firm performance.

Table 6 Hypothesis test results

Hypothesis	Paths	β	Std. dev.	T statistics	P values	Results
Hypothesis 1	SCA-> FP	0.349	0.109	3.212	0.001	Supported
Hypothesis 2	SCT x SCA -> FP	0.433	0.111	3.908	0.000	Supported

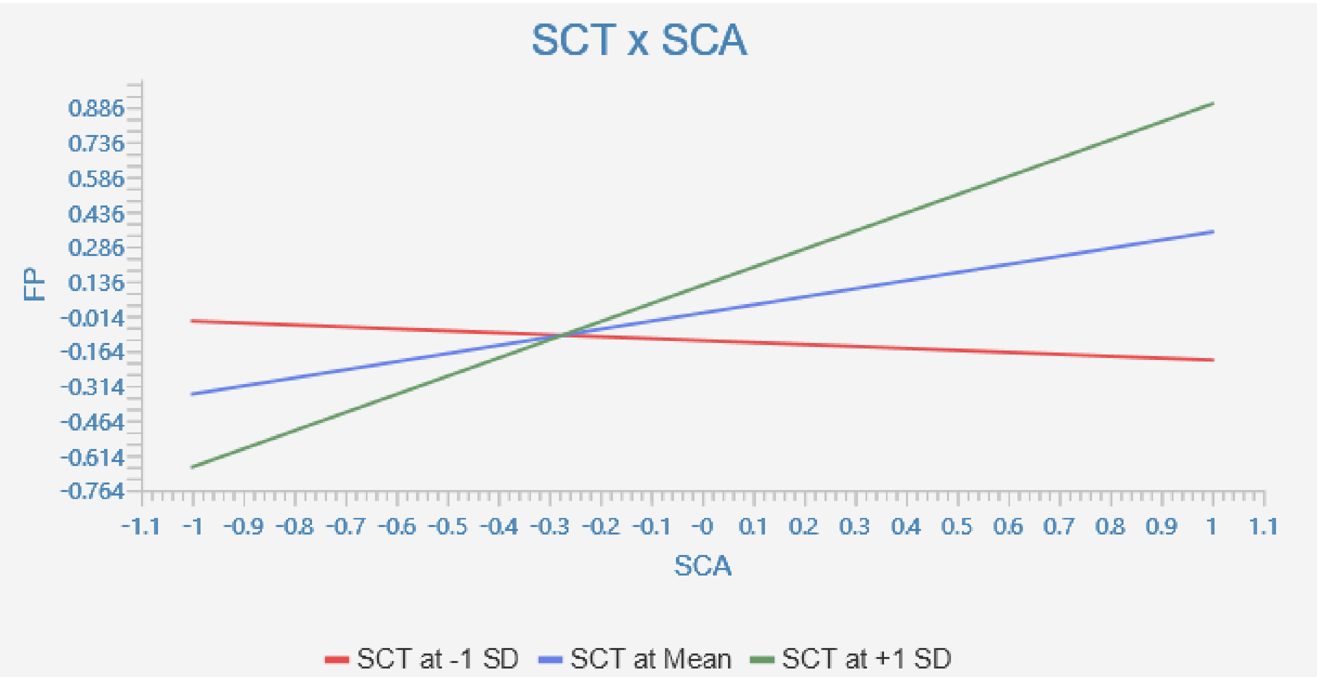

Figure 2 Moderation effect

6. IMPLICATIONS AND FUTURE RESEARCH

6.1 Managerial Implications

Analytic capabilities and data-driven decision making are becoming increasingly important for today businesses. Suggested model provides a tool for managers to better understand the impact of analytic capabilities on firm performance by considering various conditions. This can help practitioners to leverage analytic capabilities to justify investments. Our findings suggest that supply chain analytic capabilities can enhance firm performance, but the degree of enhancement is influenced by other factors and environmental changes. Overall, our research provides insights into how firms can best leverage supply chain analytics capabilities to improve performance, and highlights the importance of considering external conditions when making decisions about investments (Chen *et al.*, 2014; Germann, Lilien, & Rangaswamy, 2013; Vitari & Raguseo, 2020). This leads to a reduction in costs and heightened efficiency within supply chain processes. The results also show strong relationship between supply chain transparency and firm performance (Xu, Frankwick, &

Ramírez, 2016), moderation effect of supply chain transparency on firm performance represented in **Figure 2**.

6.2 Implications for Research

This study provides several contributions to research on supply chain analytic capabilities. First, it develops a scale for three key analytic capability constructs and their eight sub-constructs, along with measurement items, drawing on capability research in the field of supply chain data analytics (Akter *et al.*, 2016). The increasing concerns of customers and stakeholders highlight the need for the maturation of supply chain transparency research. Researchers should consider that transparency in the supply chain does not always have a positive impact on firm performance. In some cases, transparency can increase costs and affect business strategies. Additionally, revealing certain activities of some suppliers may lead to legal issues. Therefore, the impact of transparency on firm performance is dependent on the situation and how the implementation is carried out (Montecchi *et al.*, 2021).

7. CONCLUSION

Herein, this study determined the direct impact of supply chain analytics capabilities on firm performance as well as the moderating effect of supply chain transparency on this relationship. Finding of this study contributes the previous empirical studies on this subject, the impact of supply chain analytics capabilities on firm performance has been investigated by various studies (Akter *et al.*, 2016; Eckstein, Goellner, Blome, & Henke, 2015; Fosso Wamba & Akter, 2019; Fosso Wamba *et al.*, 2015; Kim *et al.*, 2012; Wamba, Gunasekaran, *et al.*, 2017) and our findings are in line with existing literature. Analysis findings show that there is a significant and positive relationship between supply chain analytics and firm performance ($\beta = 0.349$, $p<0.001$). Supply chain analytics capacity is an important concept for firms and can contribute positively to their performance. Another finding of the analysis is the moderating effect of supply chain transparency between the two variables ($\beta = 0.433$, $p<0.001$). Accordingly, when supply chain transparency is high, the relationship between supply chain analytics and firm performance is strengthened. In this model, supply chain analytics and supply chain transparency explain 38% of the variance in firm performance. Cohen (1998) considered R2 values above 33% as moderate. It can be said that this is a good ratio since there are many variables that affect firm performance. Our results shows that the adoption of a resilient supply chain analytics capabilities effectively diminishes uncertainties, elevates decision-making mechanisms, and improves information coordination across all partners within the effect of transparency and the results are align with previous researches (Huo, Qi, Wang, & Zhao, 2014; Karagülle, Çemberci, & Law, 2023; Wamba, Gunasekaran, *et al.*, 2017). To the best of our knowledge, the impact of supply chain transparency on the relationship between analytical capabilities and firm performance has not been studied.

Zhu *et al.* in 2018 revealed that supply chain analytics capabilities positively influence organizational supply chain transparency, and that supply uncertainty moderates the relationship between SCA capabilities in production and organizational supply chain transparency (Zhu *et al.*, 2018). This study approached that supply chain transparency and analytical capabilities as mutually reinforcing elements. Higher level of transparency in supply chain can provide a competitive advantage to companies by supporting the effective utilization of analytical capabilities. Our results show that there is a significant and positive moderation effect (H2), high level of supply chain transparency strengthens the relationship between supply chain analytics and firm performance.

However, this study has several limitations. Firstly, it has limited our focus to supply chain transparency as the single moderator in the relationship between supply chain analytic capabilities and firm performance, this may not be sufficient to fully capture the complex relationships at play. Also, there are other factors that can influence firm performance include the quality of a company's products or services, its marketing strategies, operational efficiency, financial management and its ability to adapt to changing conditions. Overall, firm performance is critical for the long-term success and sustainability for a company.

The companies that participated in the survey are still in the initial stages of integrating analytics capabilities into their operations. Additionally, the companies included in the study are from different sectors and based in Turkiye. Therefore, future research could benefit from collecting data from the same sectors across different countries, which could enhance the accuracy and consistency of the results.

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APPENDIX 1: SUPPLY CHAIN ANALYTICS CAPABILITIES ADAPTED FROM (FOSSO WAMBA & AKTER, 2019)

SCPL1 We continuously examine the innovative opportunities for the strategic use of supply chain analytics.

SCPL2 We enforce adequate plans for the introduction and utilization of supply chain analytics.

SCPL3 We perform supply chain analytics planning processes in systematic and formalized ways.

SCPL4 We frequently adjust supply chain analytics plans to better adapt to changing conditions.

SCID5 When we make supply chain analytics investment decisions, we think about and estimate the effect they will have on the productivity of the employees' work.

SCID6 When we make supply chain analytics investment decisions, we consider and project how much these options will help end-users make quicker decisions.

SCID7 When we make supply chain analytics investment decisions, we think about and estimate the cost of training that end-users will need.

SCID8 When we make supply chain analytics investment decisions, we consider and estimate the time managers will need to spend overseeing the change.

SCCO9 In our organization, supply chain analysts and line people meet frequently to discuss important issues both formally and informally.

SCCO10 In our organization, supply chain analysts and line people from various departments frequently attend cross-functional meetings.

SCCO11 In our organization, supply chain analysts and line people coordinate their efforts harmoniously.

SCCO12 In our organization, information is widely shared between analysts and line people so that those who make decisions or perform jobs have access to all available know-how.

SCCT13 In our organization, the responsibility for analytics development is clear.

SCCT14 We are confident that analytics project proposals are properly appraised.

SCCT15 We constantly monitor the performance of the analytics function.

SCCT16 Our analytics department is clear about its performance criteria.
SCCM17 Software applications can be easily transported and used across multiple analytics platforms.
SCCM18 Our user interfaces provide transparent access to all platforms and applications.
SCCM19 Analytics-driven information is shared seamlessly across our organization, regardless of the location.
SCCM20 Our organization provides multiple analytics interfaces or entry points for external end-users.
SCMD21 Reusable software modules are widely used in new analytics model development.
SCMD22 End-users utilize object-oriented tools to create their own analytics applications.
SCMD23 Object-oriented technologies are utilized to minimize the development time for new analytics applications.
SCMD24 Applications can be adapted to meet a variety of needs during analytics tasks.
SCBK25 Our analytics personnel understand our organization's policies and plans at a very high level.
SCBK26 Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.
SCBK27 Our analytics personnel are very knowledgeable about business functions.
SCBK28 Our analytics personnel are very knowledgeable about the business environment.
SCRK29 Our analytics personnel are very capable in terms of planning, organizing, and leading projects.
SCRK30 Our analytics personnel are very capable in terms of planning and executing work in a collective environment.
SCRK31 Our analytics personnel are very capable in terms of teaching others.
SCRK32 Our analytics personnel work closely with customers and maintain productive user/client relationships.

APPENDIX 2: SUPPLY CHAIN TRANSPARENCY WAS ADAPTED FROM (ZHU *ET AL.*, 2018)

SCT33 Our suppliers provide us with operational plans (e.g. distribution plans, production plans) regarding the products they produce for us.
SCT34 Our major suppliers provide us with detailed product design information.
SCT35 Our major suppliers collect operations information (e.g.: batch size, run quality, transfer quality, buffer stock, available machines, machine breakdown time).
SCT36 Our major suppliers share their operations information with us.
SCT37 Our major suppliers collect planning and design information (e.g.: current planning and design performance, operations performance, resource utilization, rework and scrap level, level of work progress).
SCT38 Our major suppliers share their planning and design information with us.
SCT39 Our major suppliers collect strategic information (e.g.: new orders, product demand, internal and external expertise, teachability, culture, government regulations).
SCT40 Our major suppliers share their strategic information with us.

APPENDIX 3: FIRM PERFORMANCE WAS ADAPTED FROM (AKGUN *ET AL.*, 2007; ELLINGER *ET AL.*, 2002)

FP41 Return on investment is greater than last year.
FP42 Average productivity per employee is greater than our competitors.
FP43 Our product to market time is lower than our rivals.
FP44 Market share is greater than our competitors
FP45 Sales are greater than our competitors.
FP46 Profitability (in percentage) is greater than our competitors.
FP47 The cost per business transaction is less than last year.
FP48 The number of individuals learning new skills is greater than our competitors.
FP49 Return on stockholder's equity is greater than our competitors.
FP50 Sales growth is greater than our competitors.
FP51 Operating revenues are greater than our competitors.
FP52 Return on sales (profit/total sales) is greater than our competitors.
FP53 Market value is greater than our competitor.

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