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THE ROLE OF SUPPLY CHAIN TRANSPARENCY AMONG SUPPLY CHAIN ANALYTICS CAPABILITIES

Elif CANBAZ
Dinçer Lojistik A.Ş., İstanbul, Turkey

Sümeyye ÇİÇEK VURAL
Yıldız Technical University, İstanbul,Turkey

Cemil ÇELİK
Dinçer Lojistik A.Ş., İstanbul, Turkey

Murat ÇEMBERCİ
Yıldız Technical University, İstanbul,Turkey

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Abstract:

Nowadays, to take advantage the huge amounts of data collected, companies have started to adapt analytics tools to useful insight their operations and their service level. Such companies attempt to learn from collected data about current and historical processes to define future operational decisions. Even though the importance of supply chain analytics and data-driven decision-making capabilities is recognized by companies, there is a lack of empirical studies. This study demonstrates the role of supply chain transparency (SCT) in the relation between analytics capabilities. The data were gathered from the online survey and were analyzed with partial least squares structural equation modeling (PLS-SEM) using smart-PLS. The results suggest that the existence of significant relation between analytical capabilities in plan, source and make, deliver and the mediating effect of supply chain transparency on these relationships.

Keywords:

Supply Chain Analytics Capabilities, Supply Chain Transparency, Big Data Analytics

1. Introduction

In today's highly competitive business environment, firms are being challenged by the ongoing globalization. The globalization leads to the rapid changes on customer demands and markets, business models (Chae et al., 2014). These consequences also increase the volume of generated data day by day. Research and literature about the data analytics are still in early stages. Up to date, various terms were used to define analytic capabilities that enable companies to analyze data to obtain useful insights. These terms could be listed as follows, big data analytics, supply chain analytic capabilities, business analytics (Srinivasan and Swink, 2018, Fisher et al., 2012, Agarwal and Dhar, 2014). As a result, most of the companies are planning to boost the information technology structure with Big Data solutions (Dubey et al., 2021, Raj Kumar Reddy and Gunasekaran, 2021, Davenport, 2001). Big data refers to high-volume, high-velocity, and high-variety data sets also known as 3Vs (Jha et al., 2020). These voluminous real-time and almost real-time data are regularly generated in different forms and from individual sources, such as communications (social media interactions, search engines), business (online transactions, reports, billing data), internet of things (sensors) (Jha et al., 2020, Agrawal et al., 2021, Chen et al., 2012). Over the years, data-driven decisions have received much attention in all field of business management so big data analytics provide to increase the quality of services while reducing operational costs (Moldagulova et al., 2020, Arunachalam et al., 2018). Big data impact on various businesses including retail and eCommerce, finance, advertising, logistics and transportation, natural resources (Addo-Tenkorang and Helo, 2016, Wamba et al., 2017). Among them, Logistics and

Transportation sectors are the most advantageous of the using analytics capabilities due to its dynamic processes (Borgi et al., 2017, Ittmann, 2015, Lekić et al., 2021). B2B companies like logistics require not only faster delivery but also more operational transparency. Transparency in the supply chain (SCT) is the ability to track movement of products from the manufacturer to the end-user. The main purpose is to enhance and strengthen the supply chain by ensuring that all stakeholders, including the customers, are easily accessed with product-related data (Shafiq et al., 2020). On the other hand, there is a lack of study that analytics capabilities can improve supply chain transparency as well as firm performance (Zhu et al., 2018). Herein, this study determines the role of supply chain transparency in the relation between analytics capabilities. Findings were based on a qualitative analysis of data collected 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

This study investigates potential use of supply chain analytics capabilities in various areas of supply chain operational reference model (SCOR, APICS 2017) which includes planning, making, delivery and sourcing (Trkman et al., 2010, Zhu et al., 2018, Chae and Olson, 2013).

Trkman et al. (2010) determined these areas of analytics capability as independent variables and explained their impact on supply chain performance.

Zhu et al. (2018) examined the analytics capabilities in planning indirectly impacts on supply chain transparency via analytics capabilities in source, make, and delivery (Zhu et al., 2018).

Li and co-workers investigated the positive impact on both supply chain quality performance and business performance of five decision areas (Plan, Source, Make, Deliver, and Return) of the SCOR model (li et al., 2011).

Zhou and co-workers examined the structure of supply chain processes on the SCOR model, and they empirically validate this model. Following relationships were suggested; the plan process positively impact on the source, make, and deliver processes and the mediating effect of each other (Zhou et al., 2011).

Lockamy and McCormack investigated the effects of SCOR metrics on supply chain performance, their study suggested that the planning process has a great importance to all other areas (Lockamy and McCormack, 2004).

In this research, we propose a framework of analytics capabilities in planning directly impacts on other processes (analytics capabilities in source, make, and delivery) through Supply Chain Transparency. All things considered; this study attempts to determine how supply chain transparency effect on the relationship between analytics capabilities. By examining this question, this study represents supply chain analytics capabilities can employ to enhance supply chain performance (Davis-Sramek et al., 2010, Chae and Olson, 2013).

Trkman et al. (2010) and Zhu et al. (2018) divide supply chain analytics capabilities for four categories, in this paper these categories were referred as "analytics capability in plan (ACP)," "analytics capability in source (ACS)," "analytics capability in make (ACM)," and "analytics capability in deliver (ACD)"(Zhu et al., 2018, Trkman et al., 2010). The other variable is Supply Chain Transparency (SCT).

2.1. Analytics Capability in Plan

ACP addresses to forecast customer demands and market trends. Demand prediction and supply planning play a vital role in the field of planning process (Chae and Olson, 2013). Planning is the major activity also refers to scheduling, finance, distribution (Kusrini et al., 2019b). Decisions in the planning phase could affect the whole supply chain processes, either positive or negative (li et al., 2011). Supply chain planning process should use the real-time and historical information to balance supply and demand, according to (Narasimhan and Kim, 2001) and (Fawcett et al., 2011) information sharing could improve supply chain management and integration. Literature suggests that the planning process is a critical for supply chain to achieve a firm's strategic goals (Zhou et al., 2011).

2.2. Analytics Capability in Source

ACS refers to the measure supplier performance, supplier agreements, how to manage our inventory and handle our relationship between suppliers (Hasibuan et al., 2018). ACS phase is a process that provide products and services to acquire cover the planned or actual demand (Gamoura et al., 2019, Kusrini et al., 2019a, Fosso Wamba et al., 2015). Source is critical especially for manufacturing firms. Academic researchers suggest that the long-term relationships with suppliers should be established (Chen and Paulraj, 2004, Prahinski and Benton, 2004). A better relationship with supplier lead to more accurate information and quality inputs (Zhou et al., 2011).

2.3. Analytics Capability in Make

ACM includes production processes, managing the finished-products network, equipment, and transportation (Trkman et al., 2010, Kusrini et al., 2019b). ACM step covers the entire processes of transforming the demand of the end user into the product. Moreover, ACM includes employee skills, knowledge and technology management skills for improve to customer satisfaction and competitiveness (li et al., 2011).

2.4. Analytics Capability in Deliver

ACD is process related to the distribution of services to the customer, also includes warehouses, orders, transportation. This step valuable for firm performance measurement due to its direct relationship with customer demands (Trkman et al., 2010, Zhu et al., 2018). ACD includes management systems such as transport, warehouse, order, and demand (Stewart, 1997). Capability of sharing real-time information about the products with the stakeholders and customers, as well as increasing visibility, has a vital role supply chain management (Zhou et al., 2011).

2.5. Supply Chain Transparency

Supply chain transparency covers the process information of the product from raw material to the end user (Montecchi et al., 2021, Bai and Sarkis, 2020). Source planning capabilities provide firms to evaluate supplier performance. To take advantage of analytical capabilities in source planning can boost supply chain transparency and enhance the relation with suppliers (Wang et al., 2016). In addition, inserted transparency into production process can enhance the operational efficiency (Egels-Zandén et al., 2015).

3. Research Model and Hypotheses

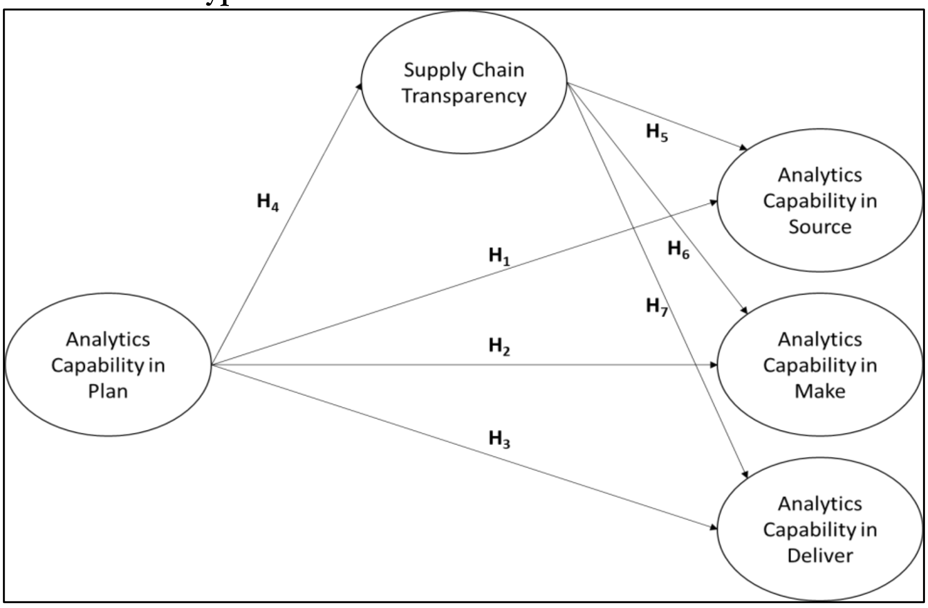

Figure 1. A Research framework of Supply Chain Analytics Capabilities

In order to measure the concepts used in the research model, some scales in the literature were adapted. To measure analytics capability in plan, source, make and deliver, and supply chain transparency, the scales adopted from (Zhu et al., 2018) were used. Supply chain planning must involve the exact demand for the product or services. Proper

planning reduces any uncertainties or misunderstandings for source planning, production planning and deliver (Lockamy and McCormack, 2004, Zhu et al., 2018). Supply chain transparency is a way in which analytics capabilities in plan impacts analytics capabilities in source, make, deliver. Both the SCOR model and the academic researchers suggest there is a relationship among the supply chain analytics capabilities (Lockamy and McCormack, 2004, Zhou et al., 2011). Effective planning processes influence the implementation of source, make and delivery processes and could enhance the supply chain transparency.
Thus, following hypotheses were proposed:
H1: There is a positive relationship between ACP and ACS
H2: There is a positive relationship between ACP and ACM
H3: There is a positive relationship between ACP and ACD
H4: There is a positive relationship between ACP and SCT
Although H1, H2, H3 directly from the SCOR model, mediating effect of SCT on these relationships can contribute the literature. Even if information sharing is easier ever than before, transparency remains challenging for the supply chain management. On the other hand, recent studies showed that transparency can improve supply chain performance under the right conditions (Kauppila et al., 2020, Ahmed and Omar, 2019, Sodhi and Tang, 2019, Montecchi et al., 2021).
H5: SCT mediates the relationship between ACP and ACS
H6: SCT mediates the relationship between ACP and ACM
H7: SCT mediates the relationship between ACP and ACD

3.1. The Analysis and Results

In this study, data were analyzed with partial least squares structural equation modeling (PLS-SEM) using smartPLS (v. 4.0.8.3.) software to test the research model. PLS-SEM can analyze multiple relationship at the same time and allows working with non-normally data and smaller sample size. For all these reasons, PLS-SEM was preferred for the analysis of the study. A two-step analysis process was followed to test the model. In the first step, the validity and reliability of the constructs were evaluated with the measurement model. Then, the hypotheses were examined in the structural model, which is the second step.

3.2. Measurement Model

To evaluate the measurement model, the reliability and validity of the model and constructs were examined according to the procedure recommended by (Hair et al., 2013). Firstly, factor loadings, Cronbach's alpha and composite reliability values were computed for each construct. According to (Hair et al., 2013) loadings should be above 0.70 and loadings below 0.40 should be removed from the model. As Table 1 shows, the majority of factor loadings were above 0.70, except for ACP7 (0.665), ACM16 (0.684) and ACM17 (0.646), which were still greater than 0.40. Next, internal consistency reliability was measured through Cronbach's alpha and composite reliability values. All constructs have Cronbach's alpha and composite reliability values above the threshold of 0.70 (Table 1). These results confirm internal consistency reliability and indicator reliability.

Table 1: Validity and Reliability of Constructs

Constructs	Items	Loadings	α	CR	AVE
Analytics Capability in Plan (ACP)			0.806	0.866	0.564
	ACP1	0.782			
	ACP2	0.793			
	ACP3	0.752			
	ACP5	0.757			
	ACP7	0.665			
Analytics Capability in Source (ACS)			0.749	0.819	0.604
	ACS12	0.711			

	ACS13	0.878			
	ACS15	0.731			
Analytics Capability in Make (ACM)			0.846	0.893	0.629
	ACM16	0.684			
	ACM17	0.646			
	ACM19	0.815			
	ACM20	0.897			
	ACM21	0.889			
Analytics Capability in Deliver (ACD)			0.845	0.897	0.686
	ACD23	0.840			
	ACD24	0.801			
	ACD25	0.931			
	ACD26	0.727			
Supply Chain Transparency (SCT)			0.885	0.921	0.744
	SCT34	0.903			
	SCT35	0.821			
	SCT37	0.875			
	SCT38	0.848			

Notes: α = Cronbach's alpha, CR = composite reliability, AVE = average variance extracted

Average variance extracted (AVE) values were calculated and all values were found greater than 0.50, indicating that constructs have acceptable convergent validity (Table 1) (Hair et al., 2013). The discriminant validity was evaluated by both Heterotrait-Monotrait Ratio (HTMT) (Henseler et al., 2015), and Fornell and Larcker Criterion (Fornell and Larcker, 1981). All the HTMT values of constructs were below the threshold level of 0.85 (Table 2). Looking at Table 3 for Fornell and Larcker criterion, AVEs' square root values (values in diagonal) were higher than respective inter-correlations (values in off-diagonal), which meets the criterion for discriminant validity. Consequently, both HTMT and Fornell-Larcker Criterion results confirm discriminant validity.

Table 2: Heterotrait–monotrait ratio (HTMT)

	ACD	ACM	ACP	ACS	SCT
ACD					
ACM	0.698				
ACP	0.735	0.694			
ACS	0.552	0.588	0.602		
SCT	0.623	0.566	0.585	0.357	

Table 3: Fornell-Larcker Criterion

	ACD	ACM	ACP	ACS	SCT
ACD	**0.828**				
ACM	0.593	**0.793**			
ACP	0.619	0.588	**0.751**		
ACS	0.498	0.544	0.567	**0.777**	

SCT	0.549	0.495	0.503	0.404	**0.862**

Note: Bold elements show square-root of the AVE

3.3. Structural Model

PLS SEM was performed to test research hypothesis. A bootstrapping procedure with 5000 bootstrap subsamples was applied using SmartPLS (v. 4.0.8.3.) To assess collinearity, Variance Inflation Factor (VIF) values were examined and all the VIF values were found below the threshold of 5. This signified there is no multi-collinearity problem with the model.

R^2 value is a measure for predictive power. It represents the amount of variance in the dependent variable explained by all the independent variable linked to it (Hair et al., 2013). The R^2 values for ACD, ACM, ACS, and SCT are 0.459, 0.399, 0.340, and 0.253, respectively. According to (Chin, 1998), R^2 values described as follows: substantial (0.67), moderate (0.33) and weak (0.19). The effect size (f2), another measure to evaluate the model, was also examined (Table 4). Effect size indicate the change in the R2 when a specified construct removed from the model (Hair et al., 2013). (Cohen, 1988) classified the effect size as small (0.02), medium (0.15) and large (0.35).

After the evaluation of the structural model, both direct and indirect paths were tested. As shown in Table 4, all the direct paths of the model H1, H2, H3 and H4 are statistically supported, and ACP is positively related to ACS (β = 0.438, p<0.01), ACM (β = 0.456, p<0.01), ACD (β = 0.460, p<0.01) and SCT (β = 0.503, p<0.01).

Table 4: Hypothesis results

Hypothesis	Paths	β	Std. Dev.	T statistics	P values	f^2	Results
H1	ACP -> ACS	0.483	0.174	2.773	0.006	0.268	Supported
H2	ACP -> ACM	0.456	0.155	2.950	0.003	0.255	Supported
H3	ACP -> ACD	0.460	0.145	3.170	0.002	0.292	Supported
H4	ACP -> SCT	0.503	0.107	4.685	0.000	0.339	Supported

To test the mediation effect of SCT the bootstrapping method was conducted. The test results of indirect paths H5, H6 and H7 are expressed in Table 5. According to findings SCT mediates the relationship between ACP and ACM (β = 0.133, p<0.10), and also ACP and ACD (β = 0.159, p<0.05). H6 and H7 are supported according to these results. However, H5 is rejected, because the mediation effect of SCT between ACP and ACS is not significant.

Table 5: Mediation Effect

	Total Effect		Direct Effect	
Path	β	P values	β	P values
ACP -> ACS	0.559	0.002	0.483	0.006
ACP -> ACM	0.590	0.000	0.456	0.003
ACP -> ACD	0.619	0.000	0.460	0.002

Indirect Effect

Hypothesis and Paths		β	Std. dev	T statistics	P values	BI [2,5%; 97,5%]	Results
H5	ACP -> SCT-> ACS	0.076	0.068	1.130	0.259	-0.101 – 0.188	Not Supported
H6	ACP -> SCT-> ACM	0.133	0.075	1.768	0.077	0.003 – 0.298	Supported
H7	ACP -> SCT -> ACD	0.159	0.075	2.117	0.034	0.029 – 0.325	Supported

4. Conclusion

The results represent that ACP is valuable for companies in implementing supply chain analytics in source, make, and deliver with mediating effect of supply chain transparency (Zhu et al., 2018). This study provides insights into the relationship between supply chain analytics capabilities (ACP, ACD, ACM, ACS) taking into consideration of SCT.

As with all survey-based studies, this study has some limitations. One of the main explanations is companies who survey participants are still in the early stages of deploying analytics capabilities into their operations. The companies

were in Turkey and operating in different sectors. So, future research is encouraged to be data collected from different countries but the same sectors. Accuracy and consistency of results could be increased.
To sum up, the results suggest that: ACP has direct and positive effect on analytics capabilities in source, make, and deliver; SCT is positively mediates the relationship between them. Nevertheless, it does not support to mediating effect on relationship between ACP and ACS. The planning phase represents to enhance a whole strategy for the supply chain management, while the source, make and deliver phases specialize in the major needs for performing that plan.

Appendix

Supply Chain Analytics Capabilities are evaluated using a 5-point Likert ranging from 1 (strongly disagree) to 5 (strongly agree)
ACP Analytics capability in plan adapted from (Zhu et al., 2018)
ACP1 Does your organization have the analytic capability to measure supply chain performance?
ACP2 Does your organization have the analytic capability to measure the impact of different supply chain strategies on supply chain performance?
ACP3 Does your organization use adequate analysis tools to inform decisions?
ACP4 Does your organization have the analytic capability to assess customer profitability?
ACP5 Does your organization have the analytic capability to assess product profitability?
ACP6 Does your organization have the analytic capability to assess variability of demand for your products or services?
ACP7 Does your organization use mathematical methods (statistics such as time series analysis) to forecast demand?
ACP8 Is a forecast developed for each product or service in your organization?
ACP9 Is a forecast developed for each customer in your organization?
ACP10 Does your demand management process make use of customer information?
ACP11 Is demand forecast accuracy measured in your organization?
ACS Analytics capability in source adapted from (Zhu et al., 2018)
ACS12 Does your organization have the analytic capability to support assessment and documentation of supplier relationships?
ACS13 Does your organization have the analytic capability to support sharing of planning and scheduling information with suppliers?
ACS14 Does your organization have the analytic capability to support collaboration with your suppliers to develop sourcing requirements?
ACS15 Does your organization have the analytic capability to measure and share supplier performance information?
ACM Analytics capability in make adapted from (Zhu et al., 2018)
ACM16 Does your organization have the analytic capability to support internal integration?
ACM17 Does your organization have the analytic capability to support updating supplier lead times monthly?
ACM18 Does your organization have the analytic capability to support the use of constraint-based management methodologies?
ACM19 Does your organization have the analytic capability to measure levels of production planning adherence?
ACM20 Does your organization have the analytic capability to support scheduling among sales, manufacturing, and distribution?
ACM21 Does your organization have the analytic capability to support the integration of your customers' planning and scheduling information with yours?
ACM22 Does your organization have the analytic capability to enabling production planning at the "item" level of detail?
ACD Analytics capability in deliver adapted from (Zhu et al., 2018)
ACD23 Does your organization have the analytic capability to track the percentage of completed customer orders delivered on time?
ACD24 Does your organization have the analytic capability to measure "out of stock" situations?

ACD25 Does your organization have the analytic capability to support assessment and documentation of distribution network relationships?
ACD26 Does your organization use mathematical tools to assist in distribution planning?
ACD27 Does your organization have the analytic capability to capture distribution management process measures?
ACD28 Does your organization have the analytic capability to assess the performance of distribution network participants?
SCT Supply Chain Transparency adopted from (Zhu et al., 2018)
SCT31 Our suppliers provide us with operational plans (e.g. distribution plans, production plans) regarding the products they produce for us.
SCT32 Our major suppliers provide us with detailed product design information
SCT33 Our major suppliers collect operations information (e.g.: batch size, run quality, transfer quality, buffer stock, available machines, machine breakdown time)
SCT34 Our major suppliers share their operations information with us
SCT35 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)
SCT36 Our major suppliers share their planning and design information with us
SCT37 Our major suppliers collect strategic information (e.g.: new orders, product demand, internal and external expertise, teachability, culture, government regulations)
SCT38 Our major suppliers share their strategic information with us

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