*Journal of International Trade, Logistics and Law, Vol. 9, Num. 2, 2023, 282-291*

# THE RELATION BETWEEN SUPPLY CHAIN ANALYTICS MANAGEMENT CAPABILITY AND FIRM PERFORMANCE

***Tuğba KARAGÜLLE***
Yildiz Technical University, Turkey

***Murat ÇEMBERCİ***
Yildiz Technical University, Turkey

Received: Oct 02, 2023 Accepted: Nov 25, 2023 Published: Dec 01, 2023

## Abstract:
*The global academic and practitioner industries have shown significant interest in the effect and importance of big data analytics and new technologies on supply chains. Based on the organizational information processing theory, this study attempts to investigate how big data driven supply chain analytics management capability influence firm performance. We tested our research hypotheses using variance based structural equation modelling with survey data collected using a web based pre-tested instrument from 201 respondents employed various industries in Turkey. The findings indicate that supply chain analytics Management capability has positive effect on firm performance.*

## Keywords:
Organizational information processing theory, supply chain analytics, big data, analytics management capability

## 1. Introduction

Companies are anticipated to manage uncertainties and risks associated with supply chain management (SCM) during disruptions, such as pandemics, wars, disasters which have the potential to damage competitive position of the firms (Bag et al., 2023) For example, the impact of COVID-19 pandemic, was beyond the disruption of supply chains, led failures of many firms. On the other hand, recent advancements in digital technologies such as IoT, AI, robotic systems, social media led organisations to deal with increasing volume, variety, and velocity (3Vs) of the data produced in real time, namely big data (Li et al, 2020). More data have not only transformed the management capabilities but also the products, and as well as the nature of supply chains (Kohli and Grover 2008, 32). SCM refers to the process of ensuring that the correct item is available in the right amount, at the right time and location, at the right price, and in optimal quality, to satisfy the customer's needs (Mallik, 2010). Supply chains (SC) are the core competence of an organisation which led the firm to reach competitive advantage and high levels of performance (Bowersox et al, 2000). In addition, SCM has been confronted with intricate challenges that have the potential to impact both efficiency and waste in SC. These challenges include fuel cost escalations, rising customer expectations, supplier inconsistency, and supply delays (Maheswari et al, 2021).

Accordingly, firm managers face significant pressure to effectively manage and enhance firm performance due to escalating complexity, uncertainty, and competition. The research indicates that the use of supply chain analytics (SCA) could have the potential to improve decision making and to take the necessary actions to get prepared for possible disruptions and market demand. Big data analytics enhances the process of decision making by enabling organizations to effectively handle uncertainty and mitigate risks (Akter et al, 2016).

Prominent companies have effectively executed many instances of SCA. Proctor & Gamble and Walmart have purportedly made significant improvements in operational efficiency by using data and analytical IT tools to make decisions on their supply chain (Davenport and Harris, 2007; Chae et al, 2014).

The SCA technologies utilize advanced analytics, artificial intelligence, and IoT to combine various aspects of product development, planning, procurement, manufacturing, logistics, and warehousing. Although the necessary requirements for utilizing business analytics have not been thoroughly examined it remains uncertain how supply

chain analytics can be employed to enhance decision-making and the competitive edge and/or performance of a company (Chen et al, 2012). Therefore, further investigation with a more comprehensive examination is required.
Several firms seem to be in the initial phase of familiarizing themselves with the significance of big data, the essential information technology (IT) and analytical expertise, the associated risks, and the process of presenting a convincing business justification for considerable investments.
While the significance of big data-driven supply chain analytics in improving firm performance has been acknowledged in operations and supply chain management literature (Akter et al., 2016), there is still a lack of understanding regarding how management capabilities can effectively address supply chain analytics capability to enhance firm performance in this highly competitive and complex environment. The primary aim of this study was to address the research question:
RQ: How does big data driven SCA Management Capability influence firm performance?
We employ the organisational information processing theory (OIPT) in conjunction with the dynamic capabilities view to enhance our comprehension of how organizations might enhance company performance. The OIPT clarifies the methods by which organizations can efficiently organize and utilize information, particularly in situations characterized by a significant degree of ambiguity (Galbraith 1974).
By investigating this question, this research contributes in several ways. Firstly, this is one of the few studies that examines that how SCA management capabilities can be utilized to increase firm performance. Second, the research analysis contributes on conceptualization of SCA management capability as higher order construct, which has been a focus in recent studies (Becker et al, 2023; Hair et al, 2023). Third, this study is carried out in Turkiye, an emerging market that is experiencing rapid growth in digital technologies and big data, giving a promising context for understanding the phenomena.
A literature review of OIPT and other current works in the field of SCM helped us come up with a theoretical model. We put this model to the test by using data from a study of Turkish managers working in different fields and structural equation modeling to find out how strong relationships were.
The following sections of the paper will be presented as follows. The research begins with examining the theoretical foundations and a brief review of the relevant literature. These serve as the groundwork for formulating the hypotheses. Following that, we outline the research methodologies, which involve gathering data through surveys and running PLS-SEM analysis. Next, we will present the findings, followed by a discussion on the theoretical and practical implications and conclusion sections.

## 2. Literature Review

### 2.1. Organisational Information Processing Theory (OIPT)

The OIPT framework has three elements: information processing capabilities (IPC), information processing needs (IPR), and the “fit” between IPR and IPC (Tushman and Nadler, 1978). Information gathering, interpretation, synthesis, and distribution capabilities are referred to as IPC. The concept of IPR refers to the gap between the information that a business requires for making decisions and the information that is accessible to the firm (Premkumar et al., 2005; Tushman and Nadler, 1978). The significance of the "fit" between IPC and IPR is emphasized by OIPT: decision makers must process a greater volume of information to attain a specified level of outcomes, in proportion to the level of uncertainty (Galbraith, 1977). In supply chain context that is the market and supplier uncertainty. Organizations must enhance their information processing capacities to get more information for improved results. This paper presents the usage of SCA Management Capability as a crucial information processing capability to convert data collected from environment into a format that can be valuable for business partners along the supply chain.

### 2.2. SCA Management Capability (SCMAC)

The idea of big data analytics (BDA) management capability, which was first developed by Kim et al. (2012), was further advanced by Akter et al. in 2016, then applied specifically to the supply chain environment and created SCMAC, as described by Fosso Wamba and Akter (2019).
BDA capability in the context of SCM, which is also named as SCAC, defined as "the capability of organizations to gather and arrange supply chain data from disparate systems dispersed throughout the organization, conduct real-time analysis, and visualize in order to establish a responsive supply chain system that facilitates decision making”

(Arunachalam et al, 2018). An analytics platform uses sensor, RFID, mobile device, click-stream, transaction, video/audio, and social media data. This diverse range of data is used to enhance insights and facilitate decision-making processes. Being one component of SCAC, SCAMC is an analytics-based capacity that helps firms gather, exchange, and analyze data in real-time to make meaningful decisions for routine and strategic tasks. SCAMC plays a vital role in the SCAC by ensuring that solid business decisions are made via the use of a well-defined management framework. The SCAMC is composed of four principles derived from Management literature: (big data driven) SCA Planning, SCA Investment Decision Making, SCA Coordination, and SCA Control (Kim et al, 2012; Wamba et al, 2017).

The SCAMC starts with a strategic SC planning process, during which SC opportunities and risks are thoroughly examined. The analytics capacity in the SC plan is centered on demand planning, which involves evaluating data to predict the market demand for goods and services (Trkman et al., 2010) and optimize resources for profitability (Chae and Olson, 2013). In order to satisfy expected needs, this calls for the capability to convert demand estimates into capacity requirements and the planning ability to coordinate supply chain processes (Wang et al., 2016). During the planning process, the potential benefits of using big data-driven models to enhance business performance are assessed (Barton and Court, 2012). Additionally, the organization must conduct ongoing evaluations of its models to ensure that they retain their predictive validity. When required, updating the models yields in-depth understanding of the modifications in the fundamental conditions that impact performance (Trkman et al, 2010).

SC investment decision; is the investment on the decision support system which can provide a distinct competitive advantage and firm performance. BDA investment decisions are critical aspects of BDA management capability as its decisions depends on cost-benefit analysis. It has also been revealed that companies who engage big investments in big data generate excess returns and gain competitive advantages.

SC coordination refers the capability that structures the cross-functional synchronization of analytics activities across the firm (Kiron et al., 2014) in which real-time information exchange will allow speedier, more flexible, and responsive supply chain processes (Ashaari et al., 2021), operations, sales and marketing to enhance overall company performance (Davenport, 2006).

SC control assures the appropriate allocation and usage of resources, such as capital and human resources. Assessing the compatibility of SCA ideas and plans, defining the duties of SCA personnel, establishing performance standards for SCA, and consistently monitoring the performance of the SCA unit.

## 3. Research Model & Hypothesis Development

### 3.1. SCA Management Capability and Firm Performance

Firm performance entails generating more economic value compared to the typical competitor in a context driven by significant market uncertainty (Petaraf and Barney, 2003). According to scholars of strategic management, "organizations allocate resources towards various IT assets including SCA tools and technology, in accordance with their strategic objectives and in pursuit of reaching higher levels of performance outcomes" (Aral and Weill, 2007). IT capabilities plays a crucial role in both the company and the supply chain's ability to respond effectively to market uncertainty (Fawcett et al, 2007), to develop information sharing (Liu et al. 2015) and ultimately leading to improved performance (Yang, 2014; Aydiner et al, 2019). OIPT suggests that businesses should enhance their information processing capacity to meet the growing demands for information processing, in order to achieve the desired outcomes (Zhu et al, 2017). The integration of IT capabilities into supply chain processes involves the ability to process information, allowing companies to understand and apply information and knowledge in ways that improve business performance (Cai et al., 2016). Monitoring and improving the performance of a supply chain has evolved into a more intricate commitment, requiring the implementation of numerous business processes, including, planning, decision-making, communication, monitoring, reporting, and feedback provision (Trkman et al., 2010). On the other hand, Big Data Analytics (BDA), has the ability to provide unique insights pertaining to diverse company patterns, operations, and market monitoring. It also facilitates exceptional predicts for enhancing overall firm performance (Mikalef et al., 2019; Fosso Wamba et al., 2020; Yasmin et al, 2020) The implementation of a robust SCA Capability, driven by big data, significantly reduces uncertainty and enhances decision-making mechanisms and information coordination among all partners. This results in cost reduction, increased efficiency of supply chain processes (Cemberci and Civelek, 2022), thus improving information processing capacity (Gunasekaran et al., 2017). The information processing theory asserts that the connection between information and its processing is the most

crucial performance aspect for an organization (Trkman et al., 2010). Based on the above and the facts of IT, BDA and SCA capabilities, we propose that:
H1: SCA Management Capability has a positive effect on Firm Performance.

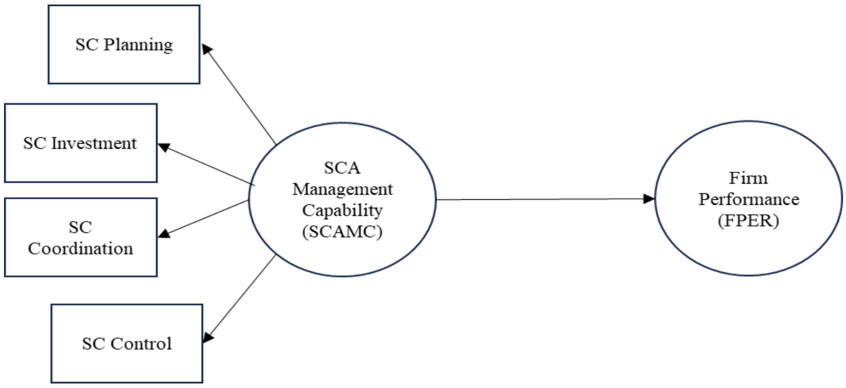


**Figure 1. Research Model**

## 4. Methodology

Partial Least Squares Path Modelling (PLS-PM) was employed for the purpose to evaluate the hypothetical model (Figure 1) with the SmartPLS4. PLS algorithm was chosen since it requires no assumptions about the data distribution. Because the questionnaire was based on a 5-point scale, detection of normality was not relevant since ordinal scales with few scale points increases skewness and kurtosis (Leung, 2011).

### 4.1. Research Design

In order to test the theoretical model, this research employs a methodology based on web-based surveys. The items used in the survey were adapted from established scales in the literature. The survey was developed using a five-point Likert scale, which included options ranging from strongly disagree (1) to strongly agree (5) (Chen & Paulraj, 2004). The survey was pretested in two stages. Firstly, five experienced industry practitioners and three researchers asked for feedback in order to ensure survey representativeness, clarity, content validity, and face validity.

### 4.2. Data Collection

After modifying the survey based on the experts' edits and recommendations, the questionnaire was distributed to supply chain professionals and top-level managers employed in Turkiye in the companies which known to utilize high technological tools including big data. The data collection was during COVID 19 outbreak period throughout the years 2020-2021. 1150 respondents were invited to attend the survey, 211 surveys returned and 10 of them was eliminated due to the misunderstandings, the response rate to the survey is 18.34 %.

**Table 1. Demographic profile of respondents**

| First-order Construct | Category | Percentage (%) |
|---|---|---|
| | College | 1 |
| Education | Undergraduate degree | 47.8 |
| | Postgraduate degree | 51.2 |
| | 0-10 years | 68.7 |
| Experience | 10-20 years | 23.3 |
| | More than 20 years | 8 |
| Industry | Financial and Insurance activities | 4.5 |

| | |
|---|---|
| Manufacturing | 36.9 |
| Transportation | 6 |
| Human health | 3 |
| Technology & Telecommunications | 11.4 |
| Energy, infrastructure | 8.5 |
| Wholesale and retail trade | 29.9 |

## 5. Data Analysis & Results

The first and second-order dimensions are reflective (Mode A), and this indicates that the mode of measurement is reflective-reflective, according to the established suggestions on building models (Ringle et al, 2012). Following the procedures of higher order modeling (Becker, 2023); two-stage approach was used to estimate the score of second-order construct. Thus, the higher-order SCMAC construct consists of all the items of the corresponding first-order latent constructs. Furthermore, the model is reflective because the theoretical direction of causality is from constructs to items.

### 5.1. Measurement Model

The study confirms the convergent and discriminant validity of the first-order measurement model using PLS path modeling (Table 2). The four first-order subdimensions; SC Planning, SC Investment Decision, SC Coordination and SC Control are encapsulated under SCMAC, the higher-order construct. Referring to Figure 1, we conducted a number of procedures to determine the convergent and discriminant validity of our model's constructs (Becker et al, 2023). As evidence of convergent validity, we observed that factor loadings were significant, with the exception of one item (FPER68.) that were eliminated from our study. Next, we determined that the extracted average variance (AVE) for each construct was greater than 0.50. According to Table 1, the loadings fall within an acceptable range and are statistically significant at the 0.01% level, which confirms corresponding reliability and convergent validity of first-order constructs (Fornell and Larcker, 1981).

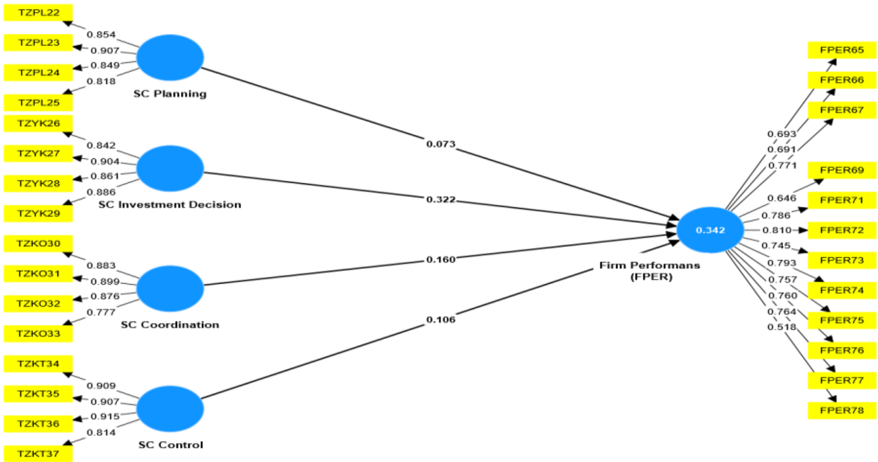


**Figure2. First-order Measurement Model**

**Table2. Assessment of first-order, reflective model**

| Reflective Constructs | Item | Loadings | Cronbach' Alpha | CR | AVE |
|---|---|---|---|---|---|
| Firm Performance | FPER65 | 0.693 | 0.92 | 0.932 | 0.536 |

| | | | | | |
|---|---|---|---|---|---|
| | FPER66 | 0.691 | | | |
| | FPER67 | 0.771 | | | |
| | FPER69 | 0.646 | | | |
| | FPER71 | 0.786 | | | |
| | FPER72 | 0.81 | | | |
| | FPER73 | 0.745 | | | |
| | FPER74 | 0.793 | | | |
| | FPER75 | 0.757 | | | |
| | FPER76 | 0.76 | | | |
| | FPER77 | 0.764 | | | |
| | FPER78 | 0.518 | | | |
| SC Coordination | TZKO30 | 0.883 | 0.881 | 0.919 | 0.739 |
| | TZKO31 | 0.899 | | | |
| | TZKO32 | 0.876 | | | |
| | TZKO33 | 0.777 | | | |
| SC Control | TZKT34 | 0.909 | 0.909 | 0.936 | 0.787 |
| | TZKT35 | 0.907 | | | |
| | TZKT36 | 0.915 | | | |
| | TZKT37 | 0.814 | | | |
| SC Planning | TZPL22 | 0.854 | 0.88 | 0.917 | 0.736 |
| | TZPL23 | 0.907 | | | |
| | TZPL24 | 0.849 | | | |
| | TZPL25 | 0.818 | | | |
| SC Investment Decision | TZYK26 | 0.842 | 0.897 | 0.928 | 0.763 |
| | TZYK27 | 0.904 | | | |
| | TZYK28 | 0.861 | | | |
| | TZYK29 | 0.886 | | | |

The Heterotrait-Monotrait Ratio (HTMT) criteria established by Henseler et al. (2015), and the criteria presented by Fornell and Larcker (1981) were taken into consideration in order to ascertain the discriminant validity. The square root of the AVE values of the research's constructs should be larger than the correlations between the research's constructs, per Fornell and Larcker's (1981) criterion. As a consequence, Table 3 displays the analysis findings based on the standards set by Fornell and Larcker (1981).

**Table 3. First-order Discriminant Validity Values – (Fornell-Larcker Criterion)**

| | Firm Performance | SC Control | SC Coordination | SC Investment Decision | SC Planning |
|---|---|---|---|---|---|
| Firm Performance | 0.732 | | | | |
| SC Control | 0.483 | 0.887 | | | |
| SC Coordination | 0.493 | 0.696 | 0.86 | | |
| SC Investment Decision | 0.55 | 0.676 | 0.656 | 0.873 | |
| SC Planning | 0.473 | 0.658 | 0.659 | 0.696 | 0.858 |

Henseler et al. (2015) defined HTMT as the ratio between the geometric means of the correlations of items of the same variable (monotrait-hetero-method correlations) and the average of the correlations of items of all the variables in the research (heterotrait-hetero-method correlations). According to the authors, HTMT values for concepts that are far apart should be less than 0.90, but preferably less than 0.85. Table 4 provides a summary of the HTMT values.

**Table 4. First-order Discriminant Validity Values (HTMT Ratio)**

| | Firm Performance | SC Control | SC Coordination | SC Investment Decision | SC Planning |
|---|---|---|---|---|---|
| Firm Performance | | | | | |
| SC Control | 0.499 | | | | |
| SC Coordination | 0.525 | 0.774 | | | |
| SC Investment Decision | 0.586 | 0.741 | 0.735 | | |
| SC Planning | 0.504 | 0.728 | 0.744 | 0.777 | |

According to the Table3 and Table 4, it is seen that the values are below the threshold value. Therefore, we can conclude that discriminant validity criteria is realized. Consequently, first-order measurement model was considered satisfactory and employed for testing the higher-order measurement model next.

Higher-order Measurement Model

Due to the hierarchical nature of the research model, we calculated the measurement properties of the second-order supply chain analytics management capability construct which represents 16 indicators. The results of the reliability, convergent and discriminant validity of the second-order measurement model is presented in Table 5, Tablo 6 and Table 7 respectively.

**Table 5. Assessment of Second-order , Reflective model**

| | Cronbach's alpha | Composite Reliability | Average variance extracted (AVE) |
|---|---|---|---|
| SCA Management Capability | 0.892 | 0.925 | 0.755 |

**Table 6. Second-order Discriminant Validity (HTMT Ratio)**

| | Firm Performance | SCA Management Capability |
|---|---|---|
| SCA Management Capability | 0.613 | |

**Table 7. Second-order Discriminant Validity (Fornell-Larcker Criterion)**

| | Firm Performance | SCA Management Capability |
|---|---|---|
| Firm Performance | 0.731 | |
| SCA Management Capability | 0.581 | 0.869 |

Overall, the evidence of adequate reliability (AVE> 0.5, CR >0.7), convergent validity (loadings > 0.5), and discriminant validity (√AVE > correlations) demonstrates the robustness of the second-order measurement model.

**5.2. Structural Model**

The structural model (Figure 2) was analyzed using partial least squares structural equation modeling (PLS-SEM), and the data were examined using the statistical software SmartPLS 4. It was preferred to use PLS-SEM because of the existence of the higher-order construct in the model (Becker et al., 2023). Within the research model, blindfolding analysis was used to predict power (Q2) and the PLS algorithm was utilized to calculate linearity, path coefficients, R2, and effect size (f2). Bootstrapping was performed to evaluate the significance of the PLS path coefficients and to determine the t-values of the sample's 5000 subsamples. Table 8 shows the R2, Q2, and VIF values for the findings.

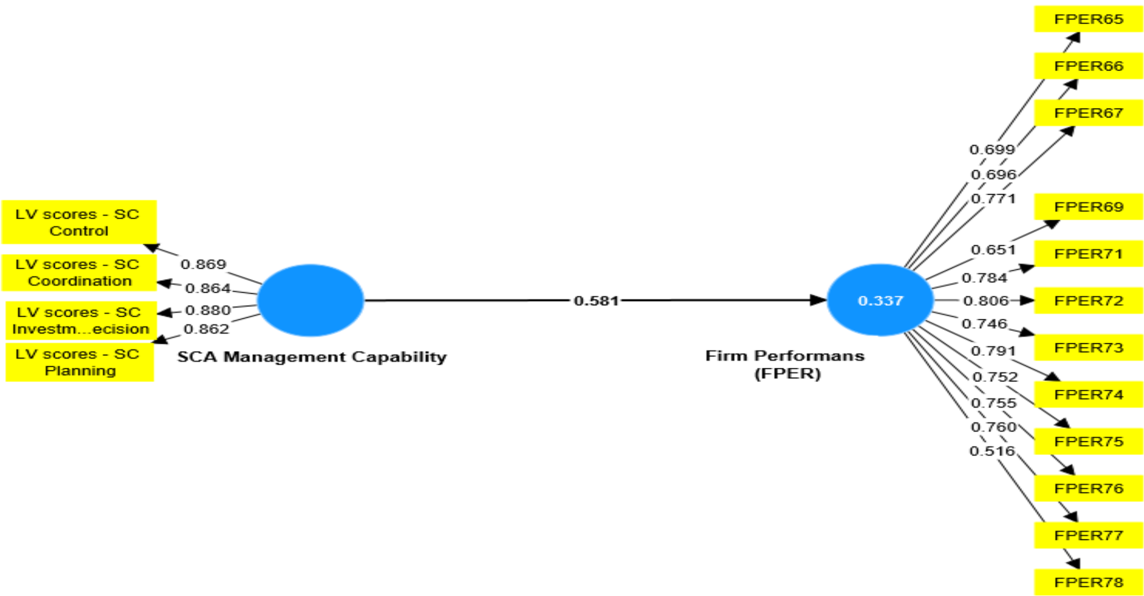


**Figure 2. Structural Model**

**Table 8. The Results of R2, and Q2**

| Constructs | | VIF | R2 | Q2 |
|---|---|---|---|---|
| SCA Management Capability | Firm Performance | 1.00 | 0.332 | 0.324 |

An analysis of the VIF (Variance Inflation Factor) values among the variables revealed that they all fell below the threshold value of 5, indicating the absence of collinearity among the constructs (Hair et al., 2014). The R2 value shows that firm performance was explained as %33.2. When the calculated predicting power coefficients of endogenous variables are greater than 0, it can be concluded that the research model has a predicting power for the endogenous variables (Hair et al., 2014). Given that the Q2 value in Table 8 is greater than zero, it can be concluded that the research model possesses the capability to estimate the firm performance.
The results of the structural relationships and hypothesis testing are presented in Table 9. The test results indicated that the firm performance was influenced by the capability of supply chain analytics management ($\beta$=0.581; $p<0.05$). Based on this result, hypotheses H1 of the research was supported.

**Table 9. Results of Structural Model**

| Main Model | Standardize β | Std. Deviation | t value | P value | Result |
|---|---|---|---|---|---|
| H1: SCAMC → Firm Performance | 0.581 | 0.052 | 11.145 | 0 | Accepted |

## 6. Theoretical and Practical Implications

The study we conducted offers significant theoretical contributions. First, it contributes to the supply chain analytics literature. Previous studies implied that one of the major contributions supply chain analytics management capability can lead organisations is to increase firm performance. To the best of our knowledge, this work is among the first empirical investigations to create and evaluate an original theoretical model that shows how SCAMC and firm performance are directly related. Second, our research confirms the potential advantage of SCA for organizational value creation in SCM by focusing on SCAMC as an information processing capability and showing its beneficial effect on firm performance. The results align with previous research indicating that the capacity to process information is crucial for effective organizational management, particularly in the field of supply chain management (Premkumar et al., 2005; Trautmann et al., 2009). Finally, the higher-order construct procedure has been employed to analyze the research model, which is a contemporary approach for investigating the acquired data.

This research also offers insights for management practices. Firstly, this research can provide precise instructions on the investment order of SCA which poses challenges and requires a significant amount of time and effort. In order to effectively manage SCA, it is necessary to establish and implement planning, decision-making, coordinating, and regulating procedures, while also ensuring efficient information processing. Furthermore, this study demonstrates that the implementation of SCA Management capability can assist managers in mitigating uncertainty in the business environment and enhancing their information processing capacity. This also supports that it is particularly crucial as managers grapple with the challenges of adapting to a dynamic business environment and striving for greater economic value (Golgeci et al, 2017). Accordingly, organizations may consider focusing on SCA investment for their business goals.

## 7. Conclusion

Businesses have a significant obstacle in dealing with the growing unpredictability in both the demand (such as the consumer market) and supply aspects of their operations. Recent research on supply chain management has emphasized the need of effectively managing demand and supply volatility via the use of supply chain analytics.

Utilizing organizational information processing theory, this research seeks to comprehend the impact of SCAMC on firm performance. A total of 201 surveys were gathered, and the research model was tested using the PLS-SEM technique. The results of SCA management capability and firm performance relationship (H1) support our expectations: the use of supply chain analytics management capability has a vital role in improving firm performance.

## References


Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016), "How to improve firm performance using big data analytics capability and business strategy alignment?", International Journal of Production Economics, 182, pp. 113–131.

Anand, A., Fosso Wamba, S. and Sharma, R. (2013), "The effects of firm IT capabilities on firm performance: the mediating effects of process improvement", 24th Australasian Conference on Information Systems, Melbourne, pp. 1-10.

Aral, S., and Weill, P. (2007), "IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation", Organization Science, 18(5), 763-780.

Arunachalam, Deepak, Niraj Kumar, and John Paul Kawalek (2018), "Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges and Implications for Practice", Transportation Research Part E: Logistics and Transportation Review, 114: 416–436.

Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A. and Liebana-Cabanillas, F.J. (2021),'Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective.', Technological Forecasting and Social Change, 173.

Aydiner, A. S., Tatoglu, E., Bayraktar, E., & Zaim, S. (2019), "Information system capabilities and firm performance: Opening the black box through decision-making performance and business-process performance", International Journal of Information Management, 47, 168-182.

Bag, S., Dhamija, P., Luthra, S. and Huisingh, D. (2023), "How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic", The International Journal of Logistics Management, 34(4), pp. 1141–1164.

Becker, J. M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023), "PLS-SEM's most wanted guidance", International Journal of Contemporary Hospitality Management, 35(1), 321-346.

Cai, Z., Huang, Q., Liu, H. and Liang, L. (2016), "The moderating role of information technology capability in the relationship between supply chain collaboration and organizational responsiveness: evidence from China". International Journal of Operations & Production Management, 36(10), pp.1247-1271.

Cemberci, M., Civelek, M. E. (2022), "The role of supply chain agility in the relationship between supply chain analytics capability and firm performance". Ulakbilge 74, 705.

Chae, B. (Kevin), Olson, D. and Sheu, C. (2014), "The impact of supply chain analytics on operational performance: a resource-based view", International Journal of Production Research, 52(16), pp. 4695–4710.

Chen, H., Chiang, R.H.L. and Storey, V.C. (2012), "Business Intelligence and Analytics: From Big Data to Big Impact", MIS Quarterly, 36(4), pp. 1165–1188.

Davenport, T.H. (2006), "Competing on Analytics", Harvard Business Review, 84(1), p.98.

Fawcett, S. E., Wallin, C., Allred, C., Fawcett, A. M., & Magnan, G. M. (2011), "Information technology as an enabler of supply chain collaboration: a dynamic-capabilities perspective", Journal of Supply Chain Management, 47(1), 38-59.

Fornell, C., Larcker, D. F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", Journal of Marketing Research, 18(1), 39-50.

Fosso Wamba, S. and Akter, S. (2019), "Understanding supply chain analytics capabilities and agility for data-rich environments", International Journal of Operations & Production Management, 39(6/7/8), pp. 887–912.

Fosso Wamba, S., Queiroz, M.M., Wu, L. and Sivarajah, U. (2020), "Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture, Annals of Operations Research, pp.1-20.

Galbraith, J. R. (1974), "Organization design: An information processing view", Interfaces, 4(3), 28-36.

Golgeci, I., Karakas, F., & Tatoglu, E. (2019), "Understanding demand and supply paradoxes and their role in business-to-business firms", Industrial Marketing Management, 76, 169-180.

Hair, Joe F., Sarstedt, Marko, Ringle, Christian M., and Mena, J. A. (2012). "An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research", Journal of the Academy of Marketing Science, 40:414–433.

Hair, J., Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2023), "Advanced issues in partial least squares structural equation modeling". SAGE Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", Journal of The Academy of Marketing Science, 43, 115-135.

Kim, G., Shin, B. and Kwon, O. (2012), "Investigating the value of sociomaterialism in conceptualizing IT capability of a firm", Journal of Management Information Systems, 29(3), pp.327-362.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014), "The analytics mandate. MIT Sloan Management Review", 55(4), 1.

Leung, S. O. (2011), "A comparison of psychometric properties and normality in 4-, 5-, 6-, and 11-point Likert scales", Journal of Social Service Research, 37(4), 412-421.

Li, Y., Dai, J. and Cui, L. (2020), "The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model", International Journal of Production Economics, 229, p. 107777.

Liu, H., Huang, Q. and Wei, S. (2015), "The impacts of IT capability on internet-enabled supply and demand process integration, and firm performance in manufacturing and services", International Journal of Logistics Management, Vol. 26 No. 1, pp. 172-194.

Mallik, S. (2010), "Customer service in supply chain management", in Bidgoil, H. (Ed.), The Handbook of Technology Management: Supply Chain Management, Marketing and Advertising, and Global Management, Vol.2, 1sted., John Wiley & Sons Inc., Hoboken, NJ.

Mandal S. (2019), "The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility", Information Technology People, 32(2):297–318

Maheshwari, S., Gautam, P. and Jaggi, C.K. (2021), "Role of Big Data Analytics in supply chain management: current trends and future perspectives", International Journal of Production Research, 59(6), pp.1875-1900.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019), "Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment", British Journal of Management, 30(2), pp. 272–298.

Peng, D.X. and Lai, F. (2012), "Using partial least squares in operations management research: A practical guideline and summary of past research", Journal of Operations Management, 30(6), pp.467-480.

Peteraf, M. A., & Barney, J. B. (2003), "Unraveling the resource-based tangle", Managerial and Decision Economics, 24(4), 309-323.

Premkumar, G., Ramamurthy, K., & Saunders, C. S. (2005), "Information processing view of organizations: an exploratory examination of fit in the context of interorganizational relationships", Journal of Management Information Systems, 22(1), 257-294.

Ringle, Christian M., Sarstedt, Marko and Straub, Detmar W. (2012), "Editor's Comments, A Critical Look at the Use of PLS-SEM in MIS Quarterly", MIS Quarterly, March, 2012, Vol. 36 No. 1, pp. iii-xiv.

Trautmann, G., Turkulainen, V., Hartmann, E., & Bals, L. (2009), "Integration in the global sourcing organization—An information processing perspective", Journal of Supply Chain Management, 45(2), 57-74.

Trkman, P., McCormack, K., De Oliveira, M.P.V. and Ladeira, M.B. (2010), "The impact of business analytics on supply chain performance", Decision Support Systems, 49(3), pp.318-327.

Tushman, M. L., & Nadler, D. A. (1978), "Information processing as an integrating concept in organizational design", Academy of Management Review, 3(3), 613-624.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. and Childe, S.J. (2017), "Big data analytics and firm performance: Effects of dynamic capabilities", Journal of Business Research, 70, pp.356.

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016), "Big data analytics in logistics and supply chain management: Certain investigations for research and applications", International Journal of Production Economics, 176, 98-110.

Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020), "Big data analytics capabilities and firm performance: An integrated MCDM approach", Journal of Business Research, 114, 1-15.

Zhu, S., Song, J., Cegielski, C. G., & Lee, K. (2017), "The impact of supply chain analytics on operational supply chain transparency: An information processing view".