IoT Value Creation Through Supply Chain Analytics Capability

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Abstract

Business Intelligence and Analytics (BI&A) systems form the key information processing artifact that enables firms to process, store, and use the data generated by the Internet of Things (IoT) in the supply chain context. We empirically investigate how firms create value from IoT through a 'capability creation' path model for Supply Chain Analytics Capability. Partial least square analysis of primary survey data collected from 127 firms in India provides two key findings: 1) a modular system architecture and decentralized governance across supply chain partners are important precursors to build a robust Supply Chain Analytics Capability which can utilize IoT based data 2) Supply Chain Analytics Capability influences Firm Performance in two ways - directly, through Supply Chain Integration, and interactively with Supply Chain Integration. Overall, this study establishes the antecedents and consequences of Supply Chain Analytics Capability, which is an important precursor to value creation through IoT.

Keywords: Internet of Things, Supply Chain Management, Analytics, Governance, Modularity, Survey research, PLS, India.

Introduction

"Data is the new oil" is a metaphor frequently used in the present context. Like oil, data must be extracted, processed, stored, and used appropriately to generate value. The Internet of Things (IoT) is a digital technology that enables firms to "extract" data in the supply chain context. Business Intelligence and Analytics (BI&A) systems form the information processing artifact that enables firms to "process, store, and use" the data generated by IoT. Thus, organizations are increasingly investing in BI&A initiatives at the supply chain level.

However, despite making such increasing investments in BI&A, many firms struggle to leverage the data handled by these systems strategically. Roughly 70% of companies fail in their analytics initiatives (King, 2018). Their challenge has been predominantly to use analytics in a manner that aligns their business strategies and value-chain activities (Elbashir et al. 2013). While BI&A have been used extensively in forward-facing contexts, such as to scan and profile customers, their use for supply chain relevant value chain activities is sparsely quoted. However, the promise of IoT lies in information integration across the supply chain, resulting in greater supply chain visibility, avoiding 'bullwhip effects,' inventory overruns, and predicting and matching supply and demand. Presumably, the use of analytics in the supply chain context should also be prominent due to the rise of IoT, the benefits of supply chain integration, and consequent organizational performance.

Implementation of analytics capabilities for supply chain management (SCM) is vital to enhance a firm's competitive advantage by improving supplier or customer relations, attaining operational flexibility, and/or by lowering production costs (Sahay and Ranjan 2008). Innovations in SCM, such as IoT-based inventory systems to track moving items in the supply chain, paired with BI&A, have helped organizations to achieve better information integration and coordination (Rai et al. 2006). Information coordination, sharing, and integration have the potential to provide better vendor and inventory management, logistical efficiencies, higher supply chain profit, and improved product innovation. BI&A that helps in supply chain integration, as a capability, is an essential factor for a firm's competitiveness and growth (Kohavi et al. 2002; Löser et al. 2008).

However, using BI&A for IoT related operations <u>within</u> a firm is not enough. In recent years, there has been an increasing rise in the use of analytics for SCM in other areas, beyond only operations management; extending to prediction, evaluation, learning, and even controlling bullwhip effects using simulated analytics tools. For example, evaluating suppliers may require analyzing several variables for each supplier to calculate supplier performance scores, which may be very difficult without BI&A tools. Implementing analytical techniques, which are one of the advanced or sophisticated processes, have the potential to improve supply chain activities and thereby improve organizational performance (Trkman et al. 2010). While necessary operations-oriented analytic capabilities form the comprehensive analytic capabilities required for improving supply chain activities within an organization, in general, additional or complex analytical capabilities provide the orientation to predict and prepare for future uncertainties. To avoid the dependencies and resulting conflicts, separate operational and advanced capabilities may be developed while allowing loosely coupled relationships to keep them independent, yet related; with only relevant standardized functions integrated.

Critically, what and where analytics applications should be implemented along the supply chain are decisions that need to be taken by the focal firm not independently, but after engaging with supply chain partners. Herein exists the critical distinction between BI&A implementation within a firm and across a supply chain. There exists significant research on issues related to BI&A value and IT governance at the intra-organizational level, where the primary agents are the IT and line functions are the primary stakeholders (Jaiswal et al. 2022; Ramakrishnan et al. 2020). However, such examinations at the supply chain level, where there are a multitude of IT and line functions across organizations, are sparse (Malik et al. 2022).

In this study, we approach the challenge of leveraging IoT analytics capabilities along the supply chain. We do that in three ways: (1) using a construct to capture *Supply Chain Analytics Capability*, (2) using an additional construct to frame and capture standardized and loosely coupled modular analytics architecture for IoT use in the supply chain, and (3) exploring what governance conditions for IoT analytics capabilities among supply chain partners have the greatest effect on firm performance.

We propose a conceptual model linking IoT related analytics and governance along the supply chain to analytical capabilities and subsequent firm performance through supply chain integration. Partial least square analysis of primary survey data collected from 127 firms in India supports the model and hypotheses.

Literature Review

BI&A capability has been studied from a variety of perspectives (Isik et al. 2011; Malik et al. 2022; Ramakrishnan et al. 2020). BI&A denotes a combination of architectures, applications, analytical tools, databases, and methodologies to support data-driven decision-making (Sharda et al. 2016). The main objective of BI&A is to integrate and analyze data from disparate sources promptly (Ramakrishnan et al. 2012). Combinations of tools and applications help to provide meaningful information to managers to understand their business better and support timely decision-making while leveraging heavily from the data collection, extraction, and analysis technologies. These, in turn, assist managers in making informed decisions. BI&A has successfully permeated various industry sectors such as airlines, banking, finance, healthcare, insurance, manufacturing, retail, securities, and telecommunications. However, a holistic implementation of BI&A capabilities across organizations in a supply chain, somewhat similar to the erstwhile enterprise resource architecture systems is sparse—partly due to the complexity of misalignment of objectives across different departments or units of an organization (Ramakrishnan et al. 2020). On the contrary, organizations are implementing specific or focused BI&A, suited appropriately to address one or two objectives for only the focal firm, such as addressing customer-oriented insights or providing higher visibility and prediction to supply chain management functions, or helping in recruitment drives. Arguably, many of these functions and the relevant BI&A applications can operate in a stand-alone manner, with minimal to moderate cross-functional dependencies (Ramakrishnan et al. 2016).

The use of BI&A in supply chain management is referred to as *Supply Chain Analytics*. Researchers have argued that the *Supply Chain Analytics* of an organization reflects the extent to which BI&A has been utilized in integrating different processes and flow of information within the firm. Thus, supply chain analytics that can glean the information from these disparate sources is required. Prior literature has examined *Supply Chain Analytics Capability* from different perspectives. Using a dynamic-capabilities framework, researchers have argued that *Supply Chain Analytics Capability* comprises data management capability, analytical process capability, and supply chain performance capability, which can improve organizational performance (Chae and Olson 2013). Similarly, prior literature in supply chain analytics has also focused on different categories of analytics, such as descriptive analytics (Choudhury et al., 2008), predictive analytics (Souza, 2014), and prescriptive analytics (Vidal et al., 2013).

Key Constructs

Supply Chain Analytics Modularity

In our study, we draw on the SCOR (supply chain operations reference) model developed by the *Supply Chain Council* (and now run by APICS) to examine the different areas of the supply chain where analytics can be used to leverage data generated through IoT. The SCOR model provides four major activities of the plan, make, source, and delivery included in supply chain management.

Supply Chain Analytics Capability is defined here as the degree to which various techniques are used to analyze IoT data for improving supply chain activities and relationships. It consists of *Planning Analytics Capability*, *Making Analytics Capability*, *Sourcing Analytics Capability*, and *Delivery Analytics Capability* based on the four activities described for supply chain management as prescribed by the *Supply Chain Council*.

Supply Chain Analytics Capability can be improved by increasing *Planning Analytics Capability*, *Making Analytics Capability*, *Sourcing Analytics Capability*, and *Delivery Analytics Capability*. *Planning Analytics Capability* refers to the use of analytics during the planning process of supply chain management. This capability helps firms predict market trends regarding their products and services. *Sourcing Analytics Capability* focuses on the procurement of raw materials and in evaluating suppliers and thereby improving supplier selection (Gangadharan and Swami 2004).

Making Analytics Capability is used in different areas, such as identifying irregularities in the production process, predicting machinery failures, scheduling the production inventory items with regards to time, belt, and batch. Thus, *Making Analytics Capability* improves the operation process of the value chain. *Delivery Analytics Capability* improves the out-bound logistics of the value chain. Thus, this capability improves the efficiency of bringing the product to the market.

Supply chain analytics thus comprises of four capabilities that can enhance the process of supply chain activities in the areas of plan, make, source, and deliver. Thus, the analytics capabilities of planning, sourcing, making, and delivery along the supply chain form the four dimensions of *Supply Chain Analytics Capability*.

An increase in either of these dimensions may increase the overall *Supply Chain Analytics Capability* without affecting the other dimension. Consider for example, the *Planning Analytics Capability*; any change in this capability will not change the capabilities of the firm to use analytics in the sourcing, making, or delivering processes (albeit, it may degrade the performance, which is an outcome, but not the capability itself). Therefore, *Supply Chain Analytics Capability* is operationalized as a second-order formative construct with *Planning Analytics Capability*, *Making Analytics Capability*, *Sourcing Analytics Capability*, and *Delivery Analytics Capability* forming the four dimensions of this construct.

Supply Chain Integration

Supply Chain Integration refers to how well the various activities are coordinated and integrated within the value chain of a firm. Supply chain in an organization chiefly deals with two types of flows: the flow of information and the flow of materials. The flow of materials from upstream to downstream has to be supported by the flow of information from downstream to upstream (and vice-versa).

Prior research has modeled the SCI constructs based on material flow integration and information flow integration (Prajogo and Olhager, 2012). Material flow integration examines the storing and flow of raw materials and finished goods between different supply chain partners. Information integration flow looks into the sharing of information between key supply chain partners. Another dimension that examines financial flow integration was also added to examine supply chain integration (Rai et al. 2006). Financial flow integration examines the interchange of financial resources amongst the supply chain partners (Rai et al. 2006).

Supply chains consist of forward- and backward- integrated activities, following which existing literature has provided multiple facets of supply chain integration. For example, prior research suggests *Supply Chain Integration* comprises of three dimensions of customer integration, supplier integration, and internal integration (Flyn et al. 2010). Internal integration refers to the data and application integration within the organization. Supplier integration refers to the coordination and sharing of information between the firm and its suppliers, whereas customer integration refers to collaboration and coordination between the organization and its customers.

Further, previous research indicates that many authors have focused on just one dimension, such as supplier integration (Cousins and Menguc, 2006; Das et al., 2006) or at internal and external integration (Saeed et al., 2005) for conceptualizing *Supply Chain Integration*. A few authors have adapted a holistic approach with a single dimension to measures integration in the supply chain (Marquez et al., 2004).

We take this holistic approach to examine *Supply Chain Integration*. In our conceptualization, a high degree of integration includes good coordination of inter-organizational activities, as well as seamless visibility across logistics value chain consisting of distribution, transportation, and warehousing facilities.

Supply Chain Analytics Modularity

Supply Chain Analytics Modularity is defined as the arrangement through which different processes and data from the different systems for the supply chain can be integrated within an organization. We examine the literature on BI&A architecture to conceptualize *Supply Chain Analytics Modularity*.

A traditional BI&A architecture comprises of a complex system consisting of a data warehouse environment, business analytics environment, performance and strategy environment, and user interface (Ramakrishnan et al. 2012; Ramakrishnan et al. 2016; Ramakrishnan et al. 2020; Sharda et al. 2016). Data warehousing involves extracting, transforming, and loading data from different disparate data sources into a data warehouse. *Supply Chain Analytics* includes a collection of tools for analyzing, manipulating, and mining the data in the data warehouse (Chae & Olson, 2013). A modular architecture for supply chain analytics provides independence among subsystems in a complex system. *Supply Chain Analytics Modularity* can be achieved through *Supply Chain Analytics Coupling* and *Supply Chain Analytics Standardization*.

Supply Chain Analytics Standardization refers to the design of supply chain analytics applications in such a way that changes made to one application does not affect the behaviors of others. Applications that follow standardized architecture are easy to install and works immediately without much difficulty. Such applications have well-defined interdependencies with the department and are easily interoperable.

Supply Chain Analytics Coupling refers to the degree to which organization-wide standards and policies pre-specify how analytics applications in an organization's portfolio connect and interoperate. Here the standards and the policies for the implementations of analytics are well established.

Further, the compliance guidelines for the line function applications are well defined. *Supply Chain Analytics Standardization* and *Supply Chain Analytics Coupling* form the two dimensions of *Supply Chain Analytics Modularity*. An increase in either may increase the overall *Supply Chain Analytics Modularity* without affecting the other dimension. Therefore, *Supply Chain Analytics Modularity* is conceptualized as a second-order formative construct.

Supply Chain Analytics Governance

We examine the literature on IT Governance to extrapolate *Supply Chain Analytics Governance*. From a business perspective, governance is about providing authority to granting decision rights, defining expectations, and ensuring performance (Pearlson and Saunders, 2013). Thus, IT Governance is all about making IT-related decisions and the distribution of these decision-making rights (Ross and Weill 2002). The literature on IT governance chiefly focuses on IT Centralization and IT decentralization choices (Tiwana and Kim, 2015).

Centralization and Decentralization refer to the degree to which the decision-making authorities regarding IT decisions lie with the IT functions and the line functions (Sambamurthy and Zmud 2000). In a highly decentralized environment, the IT-Decision making authority is shared between IT function and Line function, whereas in a highly centralized environment. IT function has the authority to make IT-related decisions. Fama and Jensen (1983) have further classified these decision rights as what objectives need to be accomplished using IT and how these objectives can be accomplished.

Prior work on IT Governance has seen different variations of these two categories of IT decision rights. For e.g. Kirsh and Beath (1996) examined IT Governance through the specification of decision rights and the implementation of decision rights. Similarly, Ross and Weill. (2002) examined the IT governance through strategic decision rights and execution of decision rights. Others examined IT governance through decision control rights and decision management rights (Tiwana 2009; Tiwana and Konsynski 2010).

In our study, we refer to *Supply Chain Analytics Governance* as the sharing of analytics related decision-making authority between the focal firm and supply chain partners. We use the two categories of specification and implementation to conceptualize *Supply Chain Analytics Governance*.

Specification decision rights refer to the decision-making authority that is given to specify the objectives of IT, whereas implementation decision rights refer to decision-making authority that is given to accomplish these objectives (Tiwana and Konsynski 2010). Therefore, the analytics specification rights include the different supply chain partners and processes that can take advantage of analytics applications. Further, it also involves the objectives, the constraints, the priorities, and the expectations of analytics for supporting the different supply chain partners.

Supply chain analytics implementation rights include decisions regarding the platform, the techniques, methods, and the programming language that needs to be used. How these two categories of decision rights are distributed across the focal firm and its partners in its supply chain is captured by the degree of centralization. Thus, *Supply Chain Analytics Specification Centralization* and *Supply Chain Analytics Implementation Centralization* form the two dimensions of *Supply Chain Analytics Governance*.

An increase in either of these dimensions may increase the overall *Supply Chain Analytics Governance* without affecting the other dimension. Therefore, *Supply Chain Analytics Governance* is conceptualized as a second-order formative construct.

Hypotheses Development

Anchoring to existing theoretical perspectives around governance and capabilities for information systems, the conceptual model (see Figure 1) for this study suggests that modularity and governance are two antecedents to developing a robust *Supply Chain Analytics Capability*.

The consequence of an effective *Supply Chain Analytics Capability* is higher *Firm Performance* through an integrated supply chain.

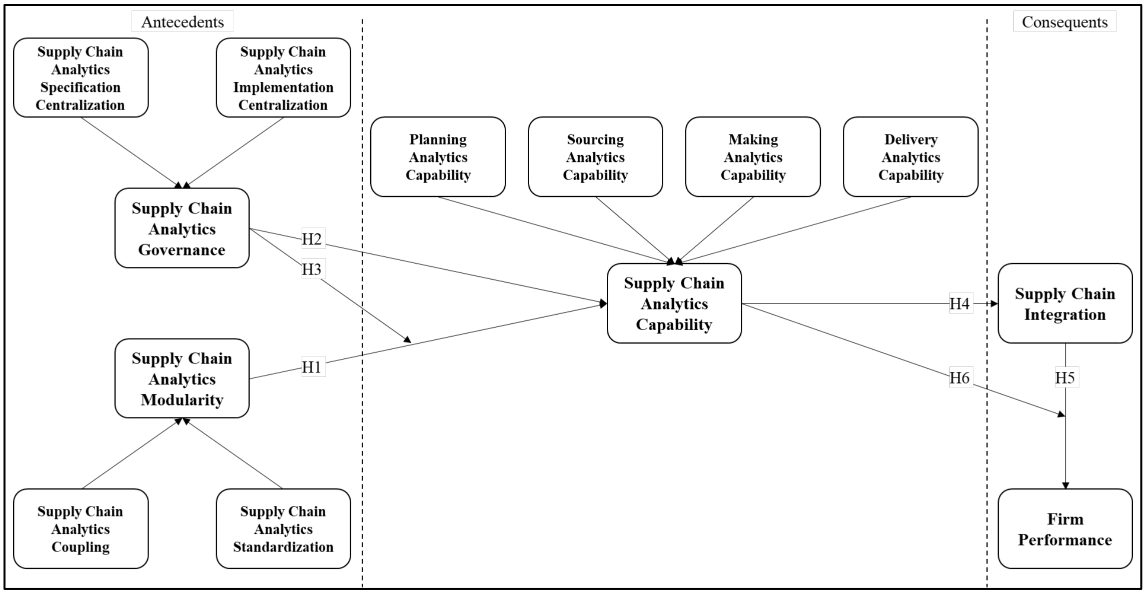

Figure 1. Conceptual Model

Supply Chain Analytics Capability is formed of the different analytical capabilities that are important to leverage the different activities within the value chain. These may require the integration of different analytical applications. The ability to add new or modified analytics components to the existing stack of analytics applications without impacting them is critical. Thus, a highly modular architecture will enable *Supply Chain Analytics Capability*, and we hypothesize:

Hypothesis (H1): There is a positive relationship between *Supply Chain Analytics Modularity* and *Supply Chain Analytics Capability*, such that an increase in *Supply Chain Analytics Modularity* is associated with an increase in *Supply Chain Analytics Capability*.

Supply Chain Analytics Governance deals with the relationship between the focal firm and its supply chain partners in deciding and implementing analytical applications for the supply chain management. Like line functions within organizations, supply chain partners are more familiar with their own operational needs (Sambamurthy and Zmud 2000). They may have a good understanding of their data, the source of their data, the analytic techniques that can provide them with better information. They are in a better position to recognize opportunities, trends, and the problems that can be solved using supply chain analytics concerning their organization (Tiwana and Konsynski 2010).

A higher supply chain analytics governance implies a higher degree of shared responsibilities between the focal firm and its partners with regards to supply chain management and, thus, more effective and efficient use of supply chain analytics. Thus, better *Supply Chain Analytics Governance* will improve the *Supply Chain Analytics Capability* of the firm. Therefore, we hypothesize:

Hypothesis (H2): There is a positive relationship between *Supply Chain Analytics Governance* and *Supply Chain Analytics Capability*, such that an increase in *Supply Chain Analytics Governance* is associated with an increase in *Supply Chain Analytics Capability*.

Even though the modularity of supply chain analytics architecture improves *Supply Chain Analytics Capability,* this relationship is stronger when it is complemented with *Supply Chain Analytics Governance*. In a supply chain, analytics systems often span different business units and are used by various departments and organizations having different needs (Ross and Weil, 2002). Further, for such systems that are interconnected across different businesses, when a change is implemented to one application, it may require IT departments to identify the effect this change may have on other inter-organizational and intra-organizational systems that interoperate with this application. Further, in order to take advantage of the four first-order *Supply Chain Analytics Capabilities* and implement effective supply chain analytics, it is important to incorporate a high level of independence among these applications while developing the modular architecture. Thus, increasing coupling when designing the supply chain modular architecture will help in enhancing *Supply Chain Analytics Capabilities*. At the same time, it is also important to have high standard interfaces that allow each of these applications to communicate with each other and with other systems such as the ERP systems, SCM systems, and the CRM systems that collect customer data and data regarding the supply chain activities. Thus, an increasing *Supply Chain Analytics Modularity* complemented with *Supply Chain Analytics Governance* will result in an improved *Supply Chain Analytics Capability*. Therefore, we hypothesize:

Hypothesis (H3): *Supply Chain Analytics Modularity* complemented with *Supply Chain Analytics Governance* has a positive relationship with *Supply Chain Analytics Capability*, such than increase in the joint effect of *Supply Chain Analytics Modularity* and *Supply Chain Analytics Governance* is associated with an increase in *Supply Chain Analytics Capability*.

A firm having a high *Supply Chain Analytics Capability* will find it easy to identify and access data and information that resides within and outside the firm (Ramakrishnan et al. 2020). High *Supply Chain Analytics Capability* provides organizations the ability to combine information from multiple internal and external sources spread across the supply chain, thereby improving *Supply Chain Integration*.

Subsequently, improving *Supply Chain Integration* can influence *Firm Performance* in many ways. Integrating the different activities within the value chain of the firm allows the firm to better respond to consumer requests and problems (Rogers et al., 1993). Seamless integration of supply chain activities can reduce lead times with suppliers (Wu et al., 2006). Information sharing due to improved *Supply Chain Integration* can lead to a reduction in the cost of inventories and demand uncertainty, thereby improving the financial performance of the firm (Frohlich, 2002).

Further, prior literature has also indicated *Supply Chain Integration* to have a positive impact on firm performance (Ataseven & Nair, 2017) as proper coordination of different activities within the value chain of a company leads to improved performance. Therefore, we hypothesize that:

Hypothesis (H4): There is a positive relationship between *Supply Chain Analytics Capability* and *Supply Chain Integration*, such that an increase in *Supply Chain Analytics Capability* is associated with an increase in *Supply Chain Integration*.

Hypothesis (H5): There is a positive relationship between *Supply Chain Integration* and *Firm Performance*, such that an increase in *Supply Chain Integration* is associated with an increase in *Firm Performance*.

Finally, we posit that *Supply Chain Analytics Capability* complements *Supply Chain Integration*. Although, *Supply Chain Integration* directly improves *Firm Performance*, having the different capabilities of the plan, make, source, and deliver strengthens this relationship because organizations can leverage *Planning Analytics Capability* to predict market trends (Trkman et al., 2010). This, complemented with coordination and integration of activities within the value chain, can enable faster response to customer requests (Rogers et al., 1993), thus improving their performance. Therefore, we hypothesize that:

Hypothesis (H6): *Supply Chain Analytics Capability,* complemented with *Supply Chain Integration,* has a positive relationship with *Firm Performance*, such that an increase in the joint effect of *Supply Chain Analytics Capability* and *Supply Chain* Integration is associated with an increase in *Firm Performance*.

Research Methodology

We conducted a cross-sectional matched-pair field survey of manufacturing organizations in India to test our research model. India is the world's fastest-growing major economy (Celly et al. 2016) and an increasing context for emergent research across varied fields of management (Kathuria and Konsynski 2012; Kathuria et al. 2018a; Kathuria et al. 2018b; Khuntia et al. 2019 (forthcoming); Ramakrishnan et al. 2020; Venkatesh et al. 2017; Venkatesh et al. 2019; Venkatesh et al. 2020; Venkatesh and Sykes 2013; Venkatesh et al. 2014).

To minimize confounding factors due to uneven economic progress across different geographical areas, we developed a sample with data for firms that were in western India. We collated multiple industry and city directories to create an initial list of more than 1,200 firms. After removing inactive organizations, defined as having no filings with India's Ministry of Corporate Affairs in the prior two years, we commenced data collection with an initial sample frame of 1000+ firms.

We utilized existing available items or developed new multi-item measures each of our first or second-order constructs. A survey is suitable for our purpose as it allows us to measure the nuances of internal firm capabilities more effectively than objective measures of implementation. Following prior research, we also used subjective measures for firm performance as differences in accounting conventions and practices and less developed accounting procedures can confound comparisons of objective financial metrics in emerging markets like India.

The questions for the survey were localized by employing the *back-translation method* (Kathuria and Konsynski 2012; Kathuria et al. 2018a; Ramakrishnan et al. 2020), wherein a bilingual research assistant translated the questions into the local language, and a second research assistant translated them back to English. The two versions were compared, discussed, and refined.

The initial items were pre-tested with four academic IS and survey research experts, and six senior IT managers as industry respondents and the questionnaires were adjusted based on the comments. Pre-test respondents offered their interpretation of the items, with a focus on content validity, terminology, and clarity. We then conducted a pilot test to assess reliability, convergent and discriminant validity, and predictability, and made final revisions to the questionnaires.

We took two steps at this stage of our research design to mitigate *common method bias*. First, we used different scales to measure different constructs, as this reduces method bias arising from commonalities in scale endpoints and anchoring effects (Podsakoff 2003). Second, we used a *matched pair design*, ensuring that independent and dependent variables were collected from different sources of information respondents in the same firm. This design also allowed us to use items suitable for each respondent.

We collected *matched-pair data* through anonymous surveys of volunteering organizations. Participation was incentivized by offering a summary of our findings and a small souvenir.

The surveys were administered using a *dual online-offline mode*, which is crucial to primary data collection efforts in India (Kathuria et al. 2018a; Khuntia et al. 2021; Khuntia et al. 2019; Ramakrishnan et al. 2020). Firms were invited to participate in the survey through emails that explained the study's purpose and benefits. This *online mode* ensured that potential respondents had Internet access and thus a basic level of technology sufficiency. Trained research assistants made four follow-up telephone calls to confirm participation and gather contact details of the two potential respondents from the firm. Surveys were then administered during in-person meetings held onsite. This *offline mode* ensured that the firm met eligibility criteria, respondents were authentic, and confidentiality concerns of respondents could be addressed.

Separate questionnaires were administered to two senior managers at each organization, to collect independent and dependent variables separately. The first questionnaire collected dependent variables concerning *Supply Chain Integration* and *Firm Performance* from the top-ranking executive responsible for and knowledgeable of the firm's strategy and performance (Managing Director or equivalent).

The second questionnaire collected independent variables concerning *Supply Chain Analytics* from the top-ranking IT executive (IT Director or equivalent). Control variables were collected from both kinds of respondents.

The *offline mode* of survey administration enabled us to identify the respondents. Organizations were dropped from the sample if either the Managing Director or the IT Director failed to respond to our survey. Similarly, if the respondent for the first questionnaire was anyone other than the Managing Director (or equivalent), and the IT Director (or equivalent) for the second questionnaire, the firm was dropped from the sample. This resulted in a final sample of 127 firms.

Data Analysis and Results

We initially conducted *t*-Test between early and late responders to check for non-response bias. The nonappearance of any statistical difference in the means of key variables for responders and non-responders and early and late responders indicated an absence of systematic bias in our data. Further, organizations that did not participate in our survey indicated a lack of time or adverse company policy regarding surveys as the reason for not doing so. The average age of respondent firms is more than 21 years, and they have an average of more than 800 employees. Note that since respondents were acting as agents of their firms in responding to firm-level questions, due to ethical principles and cultural norms, we did not collect personal information, such as demographics or job tenure. This also ensured respondent confidentiality and privacy, thereby removing legal and reputational risks associated with reporting actual, rather than the desired state of their firms (Kathuria et al. 2018a; Kathuria et al. 2018b; Khuntia et al. 2021; Khuntia et al. 2019).

Power Analysis

We use *partial least squares* (PLS), a *structural equation modeling* (SEM) technique, rather than covariance-based SEM or econometric estimation techniques to validate our model due to two reasons. First, PLS estimates interrelated dependence relationships and handles second-order formative constructs better than covariance-based SEM. Second, unlike econometric techniques, PLS also assesses a measurement model and makes no assumptions about data normality.

Although prior research has recognized a small sample size requirement as another advantage of PLS, recent work asserts that a sample size with adequate power is required. The *power analysis rule* suggests that, for our model with two independent variables and three control variables, a sample size of 122 is needed to achieve a statistical power of 80% for detecting an R^2 value of 10% with a 5% probability of error (Hair Jr et al. 2016). Thus, our sample of 127 is adequate.

Assessment of Measurement Model

Our research model consists of a mix of formative and reflective constructs. This requires us to adopt a three-step approach to assess our measurement model (Kathuria et al. 2018a) because evaluations of reflective constructs and formative constructs are different (Petter et al. 2007). For example, convergent and discriminant validity of formative constructs is assessed through the weight, sign, and magnitude of items, whereas it is assessed through item loadings for reflective constructs (Petter et al. 2007).

First, we assessed all constructs by conducting a principal components analysis with varimax rotation. This generated the expected number of factors, with high loadings (above 0.70) and low cross-loadings (below 0.30). Items that had low loadings were dropped at this stage.

CONSTRUCTS	CRONBACH'S ALPHA	AVE	COMPOSITE RELIABILITY
Supply Chain Integration	0.87	0.79	0.92
Firm Performance	0.84	0.68	0.89

Table 1. Measurement Model Assessment for Reflective Constructs

Second, we assessed the reflective constructs *Supply Chain Integration* and *Firm Performance*. We evaluated internal consistency and reliability by assessing composite reliability scores and Cronbach's α (see Table 1).

Both variables exhibited sufficiently high reliability, with satisfactory composite reliability at 0.92 and 0.89 and Cronbach's α at 0.87 and 0.84, respectively. Convergent validity was assessed by evaluating the *average variances extracted* (AVEs) and outer loadings. Both AVEs were greater than 0.50 and higher than the highest shared variance between all possible pairs of constructs for each construct.

Loadings of all retained indicators on their related theoretical constructs were significant ($p < 0.01$) and exceeded the recommended 0.70 thresholds (see Table 2). Discriminant validity was evaluated through cross-loading analysis and the *heterotrait-monotrait ratio*. Cross loadings of the indicators on other constructs are always lesser than the loading on the associated construct. The *heterotrait-monotrait ratio's* value for all constructs is below the threshold of 0.90 for inferring discriminant validity for conceptually similar constructs (Henseler et al. 2015).

ITEM	SUPPLY CHAIN INTEGRATION	FIRM PERFORMANCE
SC1	0.90	0.82
SC2	0.90	0.80
SC3	0.88	0.77
FP1	0.68	0.79
FP2	0.79	0.86
FP3	0.72	0.80
FP4	0.75	0.85

Table 2. Item Loadings for Reflective Constructs

Third, we assessed the first-order formative constructs. We assessed convergent and discriminant validity by evaluating the weight, sign, and magnitude of items (Henseler et al. 2015; Petter et al. 2007). The weights of retained indicators on their related theoretical constructs were significant at $p < 0.01$, the signs were consistent with the underlying theory, and the magnitude of the item weights were greater than 0.10. The average weight for the items was less than $\sqrt{1/N}$, with N as the number of orthogonal formative items specified.

Variance inflation factors were less than the threshold of 3.3; so multicollinearity is not a concern at the item level (Petter et al. 2007).

Finally, we performed a redundancy analysis by assessing each formative construct with a corresponding global item that summarizes it (Hair Jr et al. 2016). The path coefficients for all eight analyses were above the suggested value of 0.70. Based on these analyses, we conclude that the model provides a satisfactory fit and has adequate convergent validity, reliability, and discriminant validity.

Assessment of Second-Order Formative Constructs

We assessed the second-order formative constructs by testing for a statistically-significant path coefficient between the first-order dimensions of each second-order construct. These path coefficients represent the weights of the first-order formative constructs as they load up on the second-order constructs. The path coefficients are significant for all pairs of first-order and corresponding second-order constructs and are reported in Table 3.

Appropriateness of a formative-formative model is also demonstrated by the significant, but not high correlations among first-order constructs. Further, any alteration in a first-order construct does not cause a change in the other first-order constructs. Thus, we conclude that the proposed second-order formative constructs are supported. In summary, the measurement model and second-order construct assessments validate the psychometric adequacy of our model.

SECOND-ORDER CONSTRUCT PATH			COEF	t	p	95% CONF
SCA Coupling	→	SCA Modularity	0.57	9.50	0.00	[0.45-0.68]
SCA Standardization	→	SCA Modularity	0.52	8.68	0.00	[0.40-0.64]
SCA Specification Cent.	→	SCA Governance	0.69	17.93	0.00	[0.63-0.78]
SCA Implementation Cent.	→	SCA Governance	0.44	10.17	0.00	[0.37-0.54]
Planning AC	→	SCAC	0.43	4.53	0.00	[0.24-0.61]
Sourcing AC	→	SCAC	0.21	2.43	0.02	[0.03-0.34]
Making AC	→	SCAC	0.24	3.03	0.01	[0.11-0.44]
Delivery AC	→	SCAC	0.22	2.43	0.02	[0.05-0.39]

Table 3. Significance Test Results: Second-Order Construct Path Coefficients

Assessment of Structural Model

The structural model specifies the relationships between the theoretical constructs. We assessed the structural model by applying a *bias-corrected and accelerated bootstrapping* procedure with replacement using 5,000 subsamples.

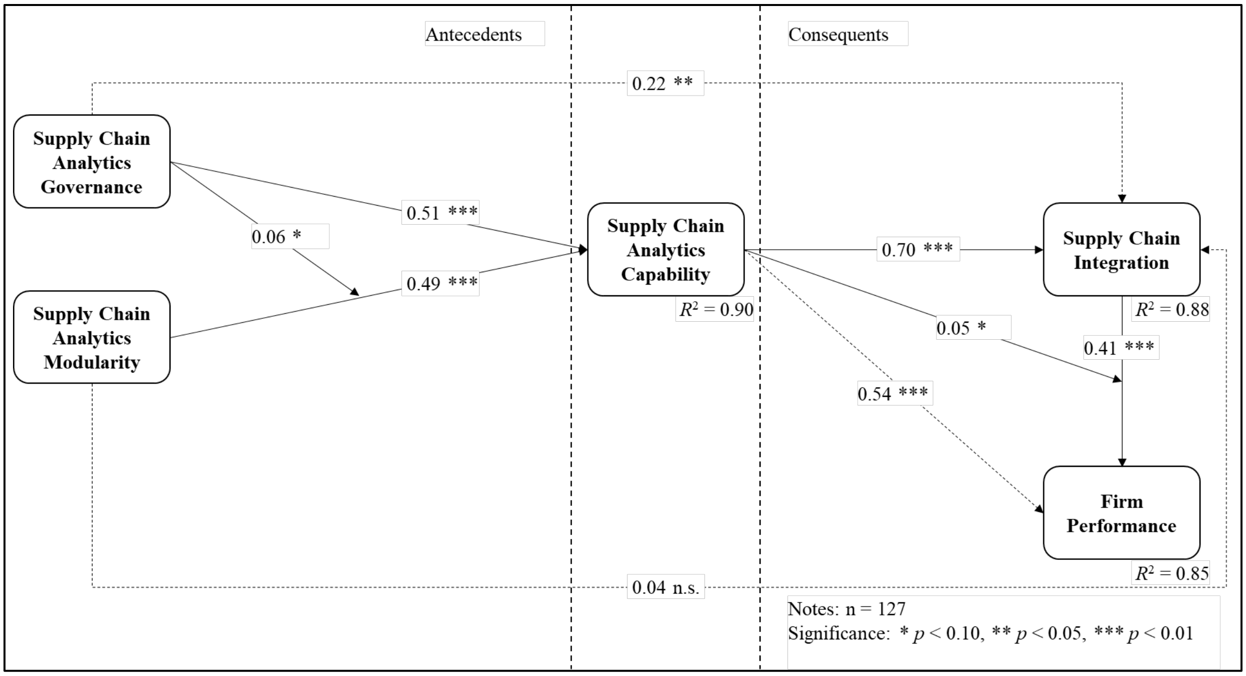

Figure 2. PLS Structural Model Results

This bootstrapping procedure relaxes normality assumptions for the distributions of individual variables, enables calculation of the statistical significance of parameter estimates, and is used for models that include mediation (Edwards and Lambert 2007). Our hypotheses were tested using a one-tailed *t*-test for *unidirectional hypotheses* through SmartPLS 3.0 (Hair Jr et al. 2016).

Since we were interested in testing the significance of both direct and moderating effects, we initially executed the analysis without the moderating paths and added the moderations in subsequent analysis, as interpreting direct effect results from a moderator model leads to misleading and incorrect evaluations (Henseler and Fassott 2010). We followed the recommended two-stage approach to create interaction terms and test our moderation hypotheses (Chin et al. 2013). Our results are displayed graphically in Figure 2 and provided in Table 4.

Antecedent / Consequent Path			H#	Coef	*t*	*p*	95% Conf	f^2	Effect
SCA Modularity	→	SCAC	H1	0.48	7.39	0.00	[0.35-0.61]	0.49	Large
SCA Governance	→	SCAC	H2	0.50	7.73	0.00	[0.37-0.62]	0.50	Large
SCA Governance & SCA Modularity	→	SCAC	H3	0.06	1.49	0.10	[0.00-0.13]	0.02	Small
SCAC	→	SC Integration	H4	0.69	7.21	0.00	[0.51-0.89]	0.41	Large
SC Integration	→	Firm Performance	H5	0.40	4.49	0.00	[0.23-0.57]	0.13	Small
SCAC & SC Integration	→	Firm Performance	H6	0.05	1.29	0.10	[0.00-0.13]	0.01	Small

Table 4. Significance Test Results: Structural Model Path Coefficients

Our results indicate that *Supply Chain Analytics Modularity* had a positive relationship with *Supply Chain Analytics Capability* (β = 0.48, t = 7.39, p < 0.01), supporting the *Modularity and SCAC* Hypothesis (H1). *Supply Chain Analytics Governance* also had a positive relationship with *Supply Chain Analytics Capability* (β = 0.50, t = 7.73, p < 0.01), supporting the *Governance and SCAC* Hypothesis (H2). Further, the joint effect of *Supply Chain Analytics Governance* and *Supply Chain Analytics Modularity,* had positive relationship with *Supply Chain Analytics Capability* (β = 0.06, t = 1.49, p < 0.10), supporting the *Governance, Modularity & SCAC* Hypothesis (H3).

Also, the relationships between *Supply Chain Analytics Capability* and *Supply Chain Integration* (β = 0.69, t = 7.21, p < 0.01) and *Supply Chain Integration* and *Firm Performance* (β = 0.40, t = 4.49, p < 0.01) are positive in support of the *SCAC and Integration* Hypothesis (H4), and the *Integration and Performance* Hypothesis (H5) respectively. Finally, the joint effect of *Supply Chain Analytics Capability* with *Supply Chain Integration* (β = 0.05, t =1.29, p < 0.10) on *Firm Performance* is significant, thereby offering support to the *SCAC, Integration and Performance* Hypothesis (H6).

Overall, the model explained ~90% of the variance in *Supply Chain Analytics Capability*, 88% in *Supply Chain Integration*, and 85% in *Firm Performance*. The R^2 for all three is greater than 75%, and hence a substantial portion of the variance of the endogenous variable is explained by our model.

In addition to evaluating the R^2 values, we assessed the *effect size*, f^2, which measures the change in R^2 when a path is omitted from the model. The relationships between *Supply Chain Analytics Modularity* and *Supply Chain Analytics Capability* (f^2 = 0.49), *Supply Chain Analytics Governance* and *Supply Chain Analytics Capability* (f^2 = 0.50), and *Supply Chain Analytics Capability* and *Supply Chain Integration* (f^2 = 0.41) all evidenced a large effect size (f^2 > 0.35). The rest of the relationships: *Supply Chain Analytics Governance & Supply Chain Analytics Modularity* and *Supply Chain Analytics Capability* (f^2 = 0.02), *Supply Chain Integration* and *Firm Performance* (f^2 = 0.13), and *Supply Chain Analytics Capability & Supply Chain Integration* and *Form Performance* (f^2 = 0.01), all had small effect sizes (f^2 < 0.15).

To assess the possibility of *multiple mediations*, we included all of the potential mediators simultaneously and considered the values and significance of their indirect effects. We also compared the indirect effects with the direct effects. This analysis yielded the following results: *SCAC* completely mediates the relationship between *SCA Modularity* and *SC Integration*, whereas it partially mediates (in a complementary manner) the relationship between *SCA Governance* and *SC Integration*. In turn, *SI Integration* partially mediates (complementary) the conceptual path from *SCAC* to *Firm Performance*.

We also test the coefficients of the non-hypothesized paths in our structural model for model completeness and rival explanations (see Figure 2). As additional robustness checks, we also retested the structural model (a) using the formative specifications of all constructs and (b) using single-item measures of all constructs. These tests yielded relationships completely consistent with our more parsimonious and conceptually sound specification.

Assessment of Common Method Bias

Although we took precautions against the threat of common method bias by using different scale anchors in the questionnaires and by employing a matched-pair data collection process, we performed three further posthoc analyses. First, we conducted *Harman's one-factor test* (Podsakoff and Organ 1986) by entering all the variables into an exploratory factor analysis. The first factor accounted for less than 30% of the variance, and no single major factor emerged. Second, we performed the *marker variable test* (Lindell and Whitney 2001) by adding a theoretically unrelated construct to the model. This did not change our results. Third, we deployed the *partial correlation method* (Podsakoff and Organ 1986) by adding the highest factor from the factor analysis to the structural model as a control variable. This did not produce a significant change in variance explained. Together, the results from the three assessments demonstrate the absence of common method bias.

Discussion

Key Findings

To summarize our results, we find that to build a robust *Supply Chain Analytics Capability*, modularity and governance are two important precursors. In addition, governance and modularity attributes have to align with each other to create a higher level of analytics capabilities. This is important, as it indicates that rather than just building a modular architecture, firms need to establish appropriate governance mechanisms with their supply chain partners when it comes to develop and execute higher orders of supply chain analytical capability, which is crucial to realizing the potential of IoT. The second set of findings suggests that *Supply Chain Analytics Capability* helps in *Firm Performance*, directly, through *Supply Chain Integration*, and interactively through integration. Thus, it is not analytics that is important, but the governance and modularity to build analytics and place it appropriately, the supply chain integration strategy is critical and important to accrue higher firm performance.

Implications for Practice

What are the managerial implications of the findings of this study? Noteworthy to mention here is that the supply chain effectively runs on appropriate predictions around demand and supply, be either inventory, raw materials, goods, or services. Prediction can be estimated based on guesses—such as consumers may demand more 'food', or 'chocolates' or 'diapers' during Holiday Season. The guess-estimation leaves the process open to be manipulated, failure, and subsequently discounted modes of selling. Be Whole Foods or Adidas; discounts are never good for firms to operate. Managers face this challenge in day-to-day operations. IoT based analytics will help in this big way, to provide accurate and established numbers to the demand and supply. Warehouse and distribution centers may be a thing of the past, if the supply chain operating in a real-time, accurate analytical path; and be highly efficient and effective to accrue higher benefits to companies. Again, warehousing and distribution is a big chunk of money for most firms.

The word caution may be that analytics need governance and modularity to develop, evolve, and get established. It may need time. It may need appropriate managerial championship and cultural change that will depend on data and information than guesswork or gut-based decision making. Operating practices of suppliers towards the focal firms need also evolve over time-based on analytical ability and exchange of information, then relationships or fixed-supply based contractual enforcements. At the same time, most suppliers are in business with multiple firms and face conflicting delivery commitments. Their work practices include regularly making more delivery commitments than they can achieve. These conflicting requirements are 'managed' by expending relational capital in the form of obfuscation, bargaining, and threats. Indeed, lack of information and visibility along the supply chain has been impediments to the ability of suppliers to operate and collaborate with firms; and has led to highly inefficient supply chain management principles—that may see a better direction with *Supply Chain Analytics* and integrated abilities of a firm.

Implications for Theory

The theoretical implications of this study are significant. Whereas previous research highlights the important role of information integration in supply chains, conflicting views exist about whether firms can really reap the benefits of such integration, and if not, what are the contingencies (Das et al. 2006; Devaraj et al. 2007; Germain and Iyer 2006). Several studies point to the contexts where, despite significant supply chain integration base, firms are not able to deliver value (Flynn et al. 2010). In this context, this study takes a 'capability creation' path model (Kathuria et al. 2018a) for *Supply Chain Analytics* and establishes why and how the capabilities can be effective for integrated performance for supply chains that utilize IoT to generate data (Baiyere et al. 2020; Wright et al. 2005). This is a major contribution of this study to information systems and supply chain literature.

Second, unlike earlier studies that focus on supply chain information integration, we demonstrate that the impacts of supply chain analytics are visible at finer levels of detail by making conceptual and empirical distinctions through the mediating roles of analytics and supply chain integration across analytics architecture and governance features towards firm performance. Although supply chain management literature has noted a few of these mechanisms, empirical investigation is sparse. This notion resonates with the broader idea in the strategy literature regarding the increasing importance of firm capabilities that enhance information technology-enabled capabilities and subsequent integration (e.g. Saldanha et al. 2020; Zhou and Li 2012). This is our second and more distinctive contribution.

Third, time and again, scholars have noted the need to study IS issues in non-US and emerging contexts (Fawcett and Waller 2015), such as GREAT (growing, rural, eastern, aspirational, transitional) economies (Dasgupta et al. 2021; Karhade et al. 2021; Karhade and Kathuria 2020). Our sample consists of respondents from India, where competition, supply chain constraints, and collaboration have intensified, resulting in significant adoption of IoT technologies. Although India, as a market, is attractive, the potential for failure, specifically due to supply chain issues, has been very high. Walmart, Amazon, and a plethora of other companies have been facing issues in the Indian markets solely because of supply chain issues. Furthermore, there is increasing literature that suggests nuances in IS theory applicability in India (Dasgupta et al. 2021; Kathuria et al. 2020; Khuntia et al. 2021; Khuntia et al. 2019; Ramakrishnan et al. 2020; Venkatesh et al. 2016; Venkatesh and Sykes 2013).

The experiences of market leaders trying to establish businesses in India point to the fact that there are idiosyncrasies in the emerging market context that need deeper investigation. This is consistent with earlier research that suggests that only specific types of capabilities are transferrable from developed to emerging markets (Hens 2012; Kathuria et al. 2020; Kathuria et al. 2018a; Kathuria et al. 2018b; Khuntia et al. 2021; Khuntia et al. 2019). Thus, our study deepens a scholarly understanding of the IS issues that lead to competitive advantage in emerging markets and for firms that operate across multiple countries (Hoehle et al. 2015; Khuntia et al. 2021; Khuntia et al. 2019; Saldanha et al. 2020; Schuetz and Venkatesh 2020; Vaithilingam et al. 2022).

While improving the elements of the supply chain, such as trucks, or roads may not be easily feasible (due to time, high costs and complexity) for firms that want to establish businesses in emerging markets, it may be feasible to build a robust IoT based supply chain information infrastructure in these countries. This is especially true in recent years as many emerging markets have considerably improved their information and communication infrastructure. For instance, India has more than 38% cell phone penetration, exceeding 20 million smartphone users (Sharda et al. 2016). Hence, the constant development of technological infrastructure coupled with high economic growth, lead to a potential capability to access, collect, and manage information through IoT across the supply chain, efficiently and effectively. Most of India is wirelessly connected, with information technology (IT access available across the country. Footprints of IT are seen in the business process of outsourcing firms in rural areas of India. Information and communication technology have changed the features of many industries, such as wheat and fishery (Ramaswamy and Gouillart 2010). Thus, although firms in emerging markets may not be able to directly improve the efficiency of the supply chain, partly due to the lack of underlying infrastructure and other impediments, with IT, firms can build a visible and efficient IoT infrastructure, powered by supply chain analytics and integration capability to leverage and improve their performance. Therein lies the premise of this study: in emerging markets, supply chain analytics systems based on modular architectures and governed collectively by supply chain partners can use IoT derived information to impact firm performance through supply chain integration – the basic tenets of upward and downward supply chain management (Brinckmann and Hoegl 2011).

Finally, while integration in supply chains has generated substantial attention in both theoretical and empirical studies, the literature provides limited evidence about the role of analytics in this integration process. This issue is highly relevant in emerging markets, as reflected in the context of this study, than developed markets (Fawcett and Waller 2015; Hult et al. 2004; Wowak et al. 2013). However, developed markets are not without supply chain integration challenges, as many firms are suffering from chronic supply chain management disorders, even after been highly successful companies for more than several decades. To highlight a few, KFC had to close many branches in the United Kingdom due to a lack of visibility of a newly integrated partner in their supply chain. The partner had trouble delivering fresh chicken to more than 900 KFC restaurants in the UK—that could devour been avoided with predicted-analytical capabilities implanted in the supply chain process[1]. Similar examples of failures are seen in the case of Target, Adidas, and other companies[2]. In this context, this study fulfills a gap by examining the antecedents of a robust supply chain analytics capability and its consequences on supply chain integration.

Limitations and Future Research

Our study has limitations, which can be starting points for future research. First, our data is collected only from firms in India, which enhances internal validity, but limits generalizability. Future work can extend the analysis to other markets. Second, this study utilizes cross-sectional data, which calls for further studies to assess and establish causality. Third, our data collection process and sampling approach might have helped us to reduce the effects of extraneous factors such as governmental regulations and uneven economic opportunities on our focal relationships; it also reduces generalizability. Future researchers can examine the applicability of our work in service contexts.

Conclusion

To summarize, Business Intelligence and Analytics systems form the key information processing artifact that enables firms to process, store, and use the data generated by the Internet of Things in the supply chain context. This paper empirically investigates how firms create value from IoT through a ‘capability creation’ path model for Supply Chain Analytics Capability. Partial least square analysis of primary survey data collected from 127 firms in India provides two key findings: 1) a modular system architecture and

[1] https://www. thebci.org/ news/supply-chain-failure-closes-more-than-half-of-kfc-fast-food-outlets.html
[2] https://channels. theinnovationenterprise.com/ articles/5-great-supply-chain-failures

decentralized governance across supply chain partners are important precursors to build a robust *Supply Chain Analytics Capability* which can utilize IoT based data 2) *Supply Chain Analytics Capability* influences *Firm Performance* in two ways - directly, through *Supply Chain Integration*, and interactively with *Supply Chain Integration*. Overall, this study establishes the antecedents and consequences of *Supply Chain Analytics Capability*, which is an important precursor to value creation through IoT. These findings broadly contribute to the emerging IS literature focusing on the areas of the Internet of Things and business analytics for the supply chain.

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