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DECLARATION

I hereby declare that this DBA dissertation is my original work and it has been written by me in its entirety.

I have duly acknowledged all the source of information which have been used in this dissertation.

This DBA dissertation has also not been submitted for any degree in any university previously.

Amit Bakshi

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Abstract

The excitement created by the introduction of Internet of things solutions (IoTS) is yet to be converted to an all-pervasive adoption and implementation across industries for capital goods in the B2B market. Proof of concepts (POC) and pilot projects are implemented but getting to the next phase of adoption and implementation across the B2B market for capital goods, has been lacking.

An exploratory mixed method is used for this research. Qualitative analysis of the semi-structured interviews with subject matter experts from users, OEMs, and service providers helped identify asset criticality, analytic intelligence, and interoperability as three core significant factors and implementation cost, vendor lock-in, and responsiveness as the interface between the core factors and adoption of IoT Solution. These factors are believed to influence the adoption of IoT Solutions, but much evidence remains conjectural or anecdotal to date. In this context, I present a systematic framework that is validated quantitatively.

The causal effect of reduction in implementation costs and vendor lock-in due to interoperability and the interaction of responsiveness on the relationship between asset criticality and IoT Solutions adoption is significant. This study is expected to provide practitioners in the B2B capital goods market insight on how to increase adoption.

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LIST OF ACRONYMS AND ABBREVIATIONS

AC	Asset Criticality
API	Application programming interface
AR	Augmented reality
ATI	Analytic Intelligence
AVE	Average variance extracted
B2B	Business-To-Business
B2C	Business-To-Customer
CITI	Collaborative Institutional Training Initiative
CPS	Cyber-physical system
CR	Composite reliability
DT	Digital Twin
EIF	European Interoperability framework
IaaS	Infrastructure as service
IACS	Industrial automation and control system
IC	Implementation Cost
ICA	Instrumentation, Controls and Automation
ICT	Information and control technology
IEC	International electrotechnical commission
IEEE	Institute of electrical and Electronics engineers
IIoT	Industrial internet of things
IO	Interoperability
IoT	Internet of things
IoTS	Internet of things Solutions
IRB	Institutional Review Board
ISA	IoT Solution Adoption
IT	Information technology
ASEAN	Association of Southeast Asian Nations
LCIM	Levels of Conceptual Interoperability model
MTBR	Mean time between repairs
MTTF	Mean time between failure
OEM	Original Equipment Manufacturer
OS	Operating System
OT	Operation technology

PHM	Prognostic and health management
POC	Proof of Concept
PSS	Product. Service system
R	Responsiveness
RUL	Remaining Useful Life
SaaS	Software as service
SME	Subject matter experts
SWEFC	Southwest Environmental Finance Center
TAM	Technology acceptance model
TCO	Total cost of ownership
TOE	Technology, Organization and Environment
VLI	Vendor Lock-in

LIST OF TERMINOLOGY

Intelligence	Intelligence provided by IoT solutions is its computational ability to obtain improvements for various difficulties. It should enable selection of the most appropriate systems based on Intelligence (Iantovics, 2021). Intelligence is the ability to apply knowledge systematically and reliably. Intelligence enables the use of knowledge to be transferred from one context to another. (Marcus, 2020).
Knowledge	Knowledge is the collection of skills and information acquired through experience or instructions from others.
Asset	Asset is an item, a thing, or an entity with potential or actual value to an organization (ISO 55000 - International Organization for Standardization). Assets are of value to an organization and are needed to meet customers' demands.
Failure	Failure occurs when the fault reaches a predetermined level. It is defined as the event that the machine is operating at an unsatisfactory level, or it can be a functional failure when the machine cannot perform its intended function at all, or it can be just a breakdown when the machine stops operating.
Mixed Method Research	Involves collecting and analyzing data, integrating the findings, and drawing reasoning from qualitative and quantitative methods in a single study (Tashakkori & Creswell, 2007).
Interoperability	Interoperability is the ability of two or more systems or components to exchange information and to use the information that has been exchanged (IEEE, Radatz J, Geraci A, Katki F, 1990)
Vendor Lock-in	Vendor Lock-in is when a customer using a product or service cannot easily transition to a competitor's product or service.
Analytics	Analytics is defined as the means to acquire data from diverse sources, process them to elicit meaningful patterns and insights, and distribute the results to proper stakeholders (Soltanpoor & Sellis, 2016).
Criticality	Criticality is the measure of risk associated with an asset. There are two main attributes in the analysis of criticality: Frequency of failure of the asset and severity of the consequence of a hypothetical failure (Javier, S. P., Márquez, A. C., & Rosique, A. S., 2016). Criticality = Frequency of Failure * Consequence of Failure

Responsiveness	Responsiveness represents the service provider's ability to respond quickly to requests and suggestions and assist customers in case of problems (Zeithaml et al.,2000).
Critical Asset	Asset having potential to significantly impact on the achievement of the organization's objectives. Assets can be safety-critical, environment critical or performance critical and can relate to legal, regulatory, or statutory requirements. Critical assets can refer to those assets necessary to provide services to critical customers. (ISO 55500:2014 – International Organization for Standardization)

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1. Introduction:

The advancements in the IoT (Internet of Things) have enabled the analytics solutions subscription model in the Business-to-Business (B2B) setting for capital goods. A key element for Industry 4.0 that will lead the manufacturing industry's digital transformation is embracing Smart machines connected and enabled by advanced analytics.

Since the early 1970's industrial automation has started with developments in electronics and computing; however, the recent advancements in information technologies comprising connectivity, communication, storage, and security are being vigorously explored for adoption by the industrial markets. The Internet has enabled connections that facilitate the transfer of data collected from sensors mounted or embedded in physical objects. The data collected from physical objects/things are digitized. They are integrated with other digital technologies like AI (Artificial Intelligence), big data analytics, cloud, and edge computing to create a CPS (Cyber-physical system) for performance improvement, cost reduction, or overall lifecycle optimization. It is also referred to as the fourth industrial revolution or Industry 4.0, where improvements in the manufacturing industry are happening due to the adoption of digital technologies with real-time characteristics. The next phase also referred to as Industry 5.0, envisages a complete digital ecosystem for the mass production of goods.

Industry 4.0 was proposed at the Hannover trade fair in 2011, and since then, few industries have adopted it. Lower costs, improved efficiencies, productivity, reduced downtime and breakdowns, better quality and safety are some benefits the industry has started experiencing due to such disruptive digital technologies. Business models consider the product as a service or subscription of capital goods based on its output or performance, service-dominant logic for business can be a reality in the near future.

The adoption of digital technologies of Industry 4.0 is fragmented, with the automotive sector having the largest adoption rate at 34% within its market sector. Other industries like energy, machinery & equipment, process, metal and mining, and electronics are still in the range of 25% to 29% (In-depth: Industry 4.0, Statista June 2021). There is still a significant gap in the adoption of Industry 4.0 uniformly across industry segments.

B2B (Business-to-Business) market is estimated to be of similar economic value as the B2C (Business -to- Consumer) (Lilien, 2016). The B2B market is characterized by the entities involved in the transaction, the marketing strategy, the approach to accomplish the transactions, and the decision-making process. B2B transactions are between manufacturers or manufacturers and a wholesaler or a retailer. In B2C marketing, emotional factors play a significant role, whereas B2B marketing is focused on a value proposition based on technical and commercial aspects. The B2C market is sometimes based on irrationality of purchase decisions, whereas in the B2B market, product features and services associated with it over the life cycle are the focal point of attention (Milichovsky, 2013).

Equipment and machinery used directly or indirectly (e.g., the utilities) to produce other goods or services, also called capital goods, are considered physical assets by the company. The capital goods business typically is a B2B business where transactions have relatively higher value, involve complexity, and multiple stakeholders such as buyers, engineers from operations, production, design, maintenance, reliability, project management, lawyers, finance & accounting. Hence B2B marketing has to consider organizational buying behavior and culture (Lilien, 2016). There are fewer customers to deal with, and the market is more heterogeneous regarding requirements and size. New solutions must be created/co-created to meet the customer's requirements and add value, especially when emerging or innovative technologies are used.

Capital goods/equipment has a design life of ten to twenty years for designed operating parameters. However, due to variability in production capacity, the equipment operates under different conditions than the design parameters. Operating the equipment at off-design conditions reduces the design life or even equipment breakdown. Accordingly, the OEMs (Original equipment manufacturers) do not have the confidence to warranty the equipment for its entire design life as they do not have visibility of the operating condition of the equipment. IoT (Internet of things) enables capabilities to capture the operating points of the equipment on a real-time basis. The availability of data on the operating conditions of the equipment to the OEM helps them monitor and provide feedback to customer engineers and operators in case of any anomalies observed. It helps improve the confidence of the OEM in the performance of the supplied equipment. Visibility and real-time monitoring of equipment's operational data also address the risks associated with performance or outcome-based contracts. At the same time, the customer/user benefit by safely operating the equipment at its optimum condition and avoiding possibilities of breakdowns or unplanned maintenance.

When IoT technology and its solutions are applied in the industrial market segment, they are referred to as IIoT or the Industrial internet of things. It combines machines and processes to monitor, collect, exchange, and analyze real-time sensor data to deliver meaningful insights (https://www.webnms.com/iot/industrial-iot-solutions.html). IoTS – Internet of Things Solutions provides the users with their assets, monitoring, predictive, preventive, and prescriptive solutions through a subscription model. It is an emerging field with the potential to change the way business will be done in the future, including the subscription of products/capital goods.

1.1 Problem Statement

The current understanding of the critical factors driving the adoption of IoTS for capital goods in the B2B market remains scant. Extant literature falls short and focuses primarily on available technologies, product capabilities, and mainly deployed case study methodology. Most of the research has been based on exploratory case study methodology considering this field as an emerging and little-understood phenomenon. The areas of studies to date have been concentrated on -

- the role of digital technologies in service business transformation
- benefits of remote monitoring
- technology adoption and usage of technology to enhance customer experience
- product, service system (PSS), and transition from product to services as additional revenue opportunities
- Service Strategies from the service providers perspective

The need to adopt and implement IoTS is evident from users' and solution providers' perspectives. However, the adoption rate of IoTS has remained low, mainly at the development or proof of concept (POC) stage. The reasons for the slow adoption rate of IoTS remain unclear. This leads to the research question –

1. What are the drivers affecting the adoption of IoT Solutions in the B2B capital goods market to transition from deployment to adoption stage in the process of technological innovation?
2. Are B2B users capable of Instrumentation, Controls, and Automation (ICA) find value from analytic intelligence provided by IoT Solutions a reason for its adoption?
3. Are there any causal links affecting the relation between the drivers for adoption and adoption of IoT Solutions?

1.2 Purpose of the Study:

This study will look at the drivers common to users and OEM/providers such that, when aligned, it will lead to adopting IoTS subscription for the capital goods in the B2B market. Since the B2B market works on the principle of a value proposition based on technical and commercial aspects, the study will focus on the technological and commercial requirements to address the adoption of IoTS as new technology in a traditional B2B market and empirically test it. The study will build upon the theoretical TAM (technology acceptance model) and TOE framework (Technology, Organization, and Environment) to investigate the factors leading to the adoption of IoT solutions in the B2B Capital goods market using an exploratory sequential design mixed-method research.

1.3 Dissertation Structure:

This dissertation is organized as per the figure below

Figure 1

Dissertation Structure

Chapter 2	Chapter 3	Chapter 4	Chapter 5	Chapter 6	Chapter 7
Literature Review	Research Model & Hypotheses	Research Method & Data Collection	Results	Discussion	Conclusion

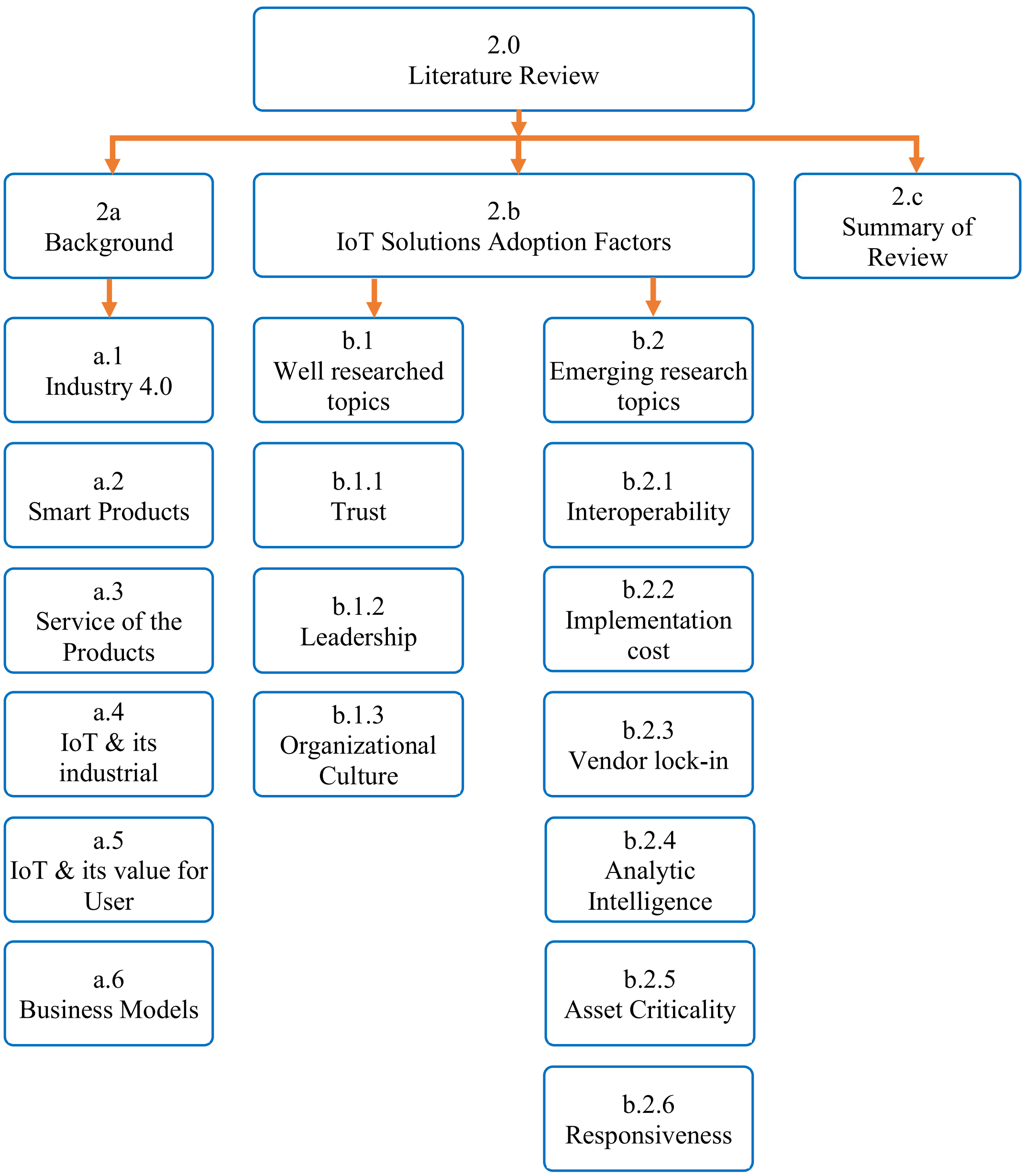
In chapter two, I first review relevant literature to set the foundation for this study. I looked at all the major factors discovered from the qualitative interviews and available research papers on those factors. In chapter three, I introduce the research context and propose the research model and several hypotheses to be tested. Chapter four includes the qualitative and quantitative methods deployed and the data collection required for analysis and hypothesis testing. The result from the data analysis is then reported in chapter five, followed by a discussion including managerial implications, future research direction, and conclusion in chapter seven.

2. Literature Review

An exhaustive literature survey has been conducted to explore the factors used in past research on adopting technological innovations like IoT Solutions, specifically in B2B industrial markets, from a user, supplier, and service providers perspective. The figure below shows the review structure and the areas the review focuses on.

Figure 2

Literature Review Structure



2a. Background

The quest of the human race to improve their lives has led to innovation and improvements, as is evident from history –

- Eighteenth-century saw the emergence of steam as a power source and its use for industrial purposes. Agriculture, the main economic activity, started getting overshadowed by mechanization in the industry using steam, referred to as the first industrial revolution.
- In the nineteenth century, oil and gas started to be used as a power source, leading to the invention of combustion engines (Nicolaus Otto, 1876). Industrial production processes saw assembly lines for mass production referred to as the second industrial revolution.
- Twentieth-century saw an emergence of automation, electronics, and computing. Repetitive, mundane human tasks started getting replaced by robots in industries. Electronics and computing helped automate processes not requiring or reducing human intervention.
- The twenty-first century is now seeing the fourth industrial revolution, where automation is networked. Machines and their workflow are connected through the intelligent network, making them operate autonomously. (Loffler and Tschiesner, 2013).

a.1. Industry 4.0

Industry 4.0, abbreviated for the fourth industrial revolution, originated from a German government initiative to promote the digitization of the manufacturing industry and was made public at the 2011 HMI fair (Hannover Messe International, for Industrial transformation). The trend involves data exchange in automated manufacturing technologies, including CPS-cyber-physical systems, IoT-internet of things, and cloud computing (Henning et al., 2013). CPS integrates machines' and humans' interactions through computing and communication technologies (Lee, E. A. (2008, May). Humans and machines are considered within the Industry 4.0 concept as an integrated socio-technical mechanism (Thoben et al., 2017). It involves the operational information being visible and actions remotely controlled through mobile devices, improving the decision-making processes (El Kadiri et al., 2016; Ahuett-Garza and Kurfess, 2018; Tao et al., 2018; Thoben et al., 2017). Human decision-making is enhanced through analytics that can provide advanced prediction, identifying events that can affect production before it happens (Schuh et al., 2017).

Industry 4.0 creates a "smart factory" (Henning et al., 2013). Digital technologies enable gathering data in real time and processing and analyzing the information to provide valuable insights (Lee et al., 2015; Wang et al., 2016). The Smart factory concept has extended from the firm-level operations over the entire supply chain – from raw material sourcing to getting the final product out to the customer. The machine-human integration is extended over the entire supply chain and product lifecycle (Wang et al., 2016; Dalenogare et al., 2018). IoT, Cloud, Big data, and Analytics are the three base technologies required for providing connectivity and intelligence for operational and market needs. The front-end technologies of connectivity and intelligence have an end-application purpose for the companies' value chain. It comprises of Smart supply chain – the way raw materials and products are delivered (Angeles, 2009); Smart products the way the products are offered (Dalenogare et al., 2018); Smart manufacturing – the way the products are manufactured and Smart working – the way humans work with emerging technologies (Stock et al., 2018). This conceptual framework of the base technologies supporting the front-end technologies has been theorized by A.G.Frank et al., 2019.

a.2. Smart Products

With the rise of IoT, the Internet of things, and "Smart Products" are being developed and gaining demand, an example, predictive maintenance of a refrigerator (Cassina et al., 2007). Novales, Mocker, and Simonovich (2016) have identified five conceptual elements that characterize this phenomenon. These are (1) hybridity or the mixture of digital and physical product components, (2) smartness or the product's context-awareness ability, (3) connectivity or the product's ability to exchange the acquired data via networks, (4) servitization and (5) the digitized product ecosystem or combining complementary products and services to reinforce the overall value offering. The products should have technological features of connectivity, monitoring, control, optimization, and autonomy to be called Smart products(Porter and Heppelmann, 2014).

Smart products enabled through IoT provide visibility to the users on the product operation and, from a servitization context, provide operational data to the manufacturers for risk assessment and potential interventions (Ardolino et al., 2018; Vendrell-Herrero et al., 2017). The term servitization was coined by Rada and Vandermerwe (1988), and it is defined as the process of creating value by adding services to products. The shift towards offering services coupled with products refers to servitization Baines et al. (2007) and Neely (2007). Along similar lines, a combination of products and services in a system that provides functionality for consumers and reduces environmental impact is defined as Product-Service-System – PSS (Goedkoop et al., 1999; Tukker, 2004). Both Servitization and PSS concepts overlap as they involve services for the product supplied by the manufacturer. Service characteristics are very different from the product as service is intangible, perishable, and inseparable from the product and thus poses a challenge to forming strategies in service marketing (Zeithaml et al. 1985). For service requirements, the dependence and interdependence between exchange partners generally substantially affect continuing relationships more than products. Firms and customers are more involved in the production and consumption of services than physical goods (Zeithaml et al. 1985).

a.3. Service of the Products

"Service is recognized as a core source of value itself." More profoundly, service should be the dominant logic driving all marketing (Vargo & Lusch 2004). Servitization brings collaboration between the firm and customer to gain an advantage from the laws of synergy; enterprises gain a competitive advantage as the value of resources, related skills, and competencies exceed the sum of the assets (Opresnik & Taisch, 2015).

Technology is accelerating the shift of attention towards value-added services from the product. Emerging research exploring the intersection between the IoT and servitization domains is captured by the 'digital servitization' notion (Vendrell-Herrero, Bustinza, Parry, & Georgantzis, 2017). Manufacturers carry the risks intrinsic to servitization, including asset availability, reliability, and performance commitments that can be managed by IoT's capability to transfer the data available from sensors mounted on the assets, enabling remote monitoring of product performance (Rymaszewska et al., 2017, Benedettini, Neely, & Swink, 2015; Hasselblatt, Huikkola, Kohtamäki, & Nickell, 2018). Non-availability of a product or its sub-optimal performance is the risk transferred from customer to supplier, which is the value proposition of servitization (Grubic & Jennions, 2018). The IoT enables servitizing manufacturers to develop fault awareness, improve maintenance, enhance equipment design to cut existing faults, simplify maintenance activities, and inform operator behavior (Ardolino et al., 2016; Lightfoot et al., 2011).

IoT is pervasive in implementing any service transformation strategy thanks to its ability to capture, scrutinize, and transmit data. It allows the manufacturer to move the focus from their products toward customers' requirements. The strategies shift to product usage in the customer operational environment, helping them meet or exceed customer needs. The strategies for providing services are categorized into four different types depending on whether they are provided for the company's own supplied product or on product supplied by another company – (a) services for own products, (b) operations and services on own products, (c) services for own and third-party products and (d) diagnostic operations services (Raddats & Easingwood, 2010).

Service characteristics like intangibility and perishability require a different treatment from the marketing perspective (Shostack, 1977). A production line approach to providing service will improve quality and efficiency (Levitt, 1972). Industrializing services in a service factory will standardize innovation, development, and operations. A service factory is a knowledge hub of innovation and serving customers (Chase & Garvin, 1989). Industrializing services or having a production line approach are efforts to standardize the service offerings for benefits of scale, assuming that the customers' requirements are homogeneous. However, when demand is heterogeneous, the personalization of services is required to satisfy customer requirements. Personalization uses customer information to give an adaptive service offering for specific customer requirements (Heim and Sinha, 2005). Technology enables the flow of information and big data analytics to provide personalized service. Service can be personalized more with a higher degree of advanced technology. (Rust & Huang, 2012 & 2014). Services evolve from standardized to personalized when co-creation happens over time (Rust & Huang, 2014).

a.4. IoT & its industrial applications

Changes in the environment can make the core capabilities obsolete (Levitt & March 1988). The organization's long-term performance requires renewal, reconfiguration, and recreation of dynamic capabilities and resources (Opresnik & Taisch, 2015). IoT links the physical goods and intangible services together as a network keeping the customer requirements at the center of this service network (Huang & Rust, 2017). According to Tec. News (2016), the key to success in modern industry is to provide high-end quality services or products at the lowest cost, and industrial factories are trying to improve performance as much as possible to increase their profits and reputation. It can be achieved by using various data sources that provide useful information regarding different aspects of the factory. In this stage, data utilization to understand the current operating conditions and detect faults and failures is an important topic for research (Sung, 2018).

Technology advances in sensors, wireless connectivity, and real-time predictive analytics enable enterprises to provide added value insights (Camarinha-Matos et al. 2013). Technological development drives costs down, moving industries towards higher information content in their products and processes (Porter and Millar, 1985; Porter and Heppelmann, 2015). Data-driven decision-making ahead of time provides strategic value to data analysis. Predictions from data analysis drive increased situational awareness and proactive decision-making (Engel, Etzion, & Feldman, 2012). Proactive decision-making goes beyond real-time predictive analytics by providing recommendations based on predictions ahead of time (Bousdekis et al., 2018).

IoT enables continuous feeds of context-aware data; cloud computing facilitates the deployment of large 'data lakes' (IaaS – Infrastructure as Service) and applications (SaaS-software as service) used to process data and share information. The combination of IoT, cloud computing, and predictive analytics is vital for generating new knowledge. (Ardolino et al., 2018). Manufacturers monitor products remotely for their location, condition, and use (Baines and Lightfoot, 2014). The typology of remote monitoring has four levels: monitoring, detection, diagnostic and prognostic (Jardine, Lin, & Banjevic, 2006). The key principle is enriching physical products with digital components (Novales et al., 2016) and enabling real-time monitoring, acquisition, and communication of the product's performance in service

(Grubic, 2014). The architecture of the IoT is considered at three levels: end devices (sensors, actuators), propagator codes (ensuring transport and gateways to the traditional Internet), and integrator functions (enabling analysis and control).

IoT is an emerging technology with new features and applications being continuously developed. Augmented and virtual reality are two emerging technologies that create partial and complete virtual environments (Elia et al., 2016; Gilchrist, 2016). Augmented reality (AR) finds applications in e-commerce companies where enriching customer experience and enhanced intuitive interface are required (Tabusca, 2015). AR facilitates customer experiences, engagement, and awareness on e-commerce platforms while online shopping (O'Brien, 2010).

In manufacturing maintenance, virtual reality accelerates workers training with an immersive simulation of the maintenance routines (Gorecky et al., 2017; Turner et al., 2016), while augmented reality supports workers with interactive and real-time guidance for the necessary steps of the tasks to be made (Tao et al., 2018). In product development activities, these tools create virtual models of the product, helping to detect flaws during product usage without needing physical prototypes (Tao et al., 2018; Guo et al., 2018).

Predictive Analytics techniques are used to set anticipated or pre-emptive actions – such as issuing preventive maintenance or shipping spare parts. (Ardolino et al., 2018). IoT is a foundational requirement for the manufacturers or service providers who perform one or both roles of being an availability provider and a performance provider. IoT technology is a critical tool for asset management companies because the complexity and size of their infrastructure require a new way of gathering data and monitoring systems (Hua et al., 2014; Lee, 2014). Performance providers rely on predictive analytics and extract knowledge from installed products' data to develop advanced services (Baines & Lightfoot, 2013). Decision-making processes focus on preventing malfunction, asset failure, or quick assessment of infrastructure damage after an event so that maintenance procedures can be directed to the areas that need immediate attention (Aono et al., 2016).

From a user's perspective, they need to forecast machinery failures, overloads, or any other problem to prepare and plan for such eventuality in advance. It will help to avoid downtimes due to unexpected failures during the operation. Machines with artificial intelligence can also automatically identify product nonconformities in earlier stages of the production process, improving quality control and reducing production costs (Tao et al., 2018). Information generation algorithms must detect and address invisible issues, including machine degradation and component wear (Lee et al., 2013, 2014). Product monitoring also provides vital information for manufacturers to identify product usage patterns for market segmentation and new product development (Zhong et al., 2017; Ayala et al., 2017).

a.5. IoT & its Value for User

Value creation is the ultimate purpose and the central process of economic exchange (Vargo et al., 2008). IoT-based solutions enable firms to get closer to their end customers by creating a cost-effective value proposition, relieving customer pains, and consequently improving profitability (Rymaszewska, Helo & Gunasekaran (2017). Additional value of convenience, timesaving, simplified information processing, reduced perceived risks, and maintaining a state of psychological comfort is received as an additional value by both the firm and the customer (Sheth and Parvatiyar 2000; Verma et al. 2016). Higher product availability is the real value of technologies like remote monitoring enabled through IoT (Oliva & Kallenberg, 2003). IoT finds applications in various industries, including retail, manufacturing, healthcare, insurance, home appliances, heavy equipment, airlines, and logistics (Lee & Lee, 2015).

Besides various applications mentioned earlier, IoT finds application in various other sectors, including the much-cited "big three" aero-engine manufacturers Rolls Royce, GE, and Pratt and Whitney, providing engine health management (Smith, 2013). IoT applications enabling monitoring and control, big data and business analytics, information sharing, and collaboration create and enhance customer value (Lee & Lee, 2015). Internal traceability (Angeles, 2009; Wang et al., 2016), energy management - monitoring and improving energy efficiency (Henning et al., 2013), (additive manufacturing using 3D printing of digital models for manufacturing different goods (Weller et al., 2015; D'Aveni, 2015) are other examples of applications using IoT. Connected devices and the rapid exchange of information will result in increased manufacturing productivity, a shift in economics, and a modified workforce profile, which will ultimately result in a profound change in the competitiveness of companies and regions (Rüßmann et al., 2015)

IoT appears to have emergent features. Many more and varied applications are expected to use IoT technologies. Affordance theory is recommended to investigate the link between the IoT and its diverse outcomes. It is based on the notion that regardless of its design, opportunities for different uses of an artifact can be realized by an actor (Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007).

a.6. Business Models

A business model suggested monetizing IoT investments include a combination of products and services (Ardolino, Saccani, Gaiardelli, & Rapaccini, 2016; Hsu, 2007; Rymaszewska, Helo, & Gunasekaran, 2017). Manufacturers servitize to improve their profit margins, create a barrier for competitors, create sustainable competitive advantage, and meet market requirements (Bustinza, Bigdeli, Baines, & Elliot, 2015; Porter & Ketels, 2003; Raddats, Baines, Burton, Story, & Zolkiewski, 2016). Firm service strategies lead to offering service bundles that may include a warranty, spare parts, repair, maintenance, operator training, condition monitoring, in-field services, customer support agreements, and outcome-based contracts (Lightfoot & Baines, 2014). IoT facilitates communication between objects and systems in a factory; cloud services provide access to information and services. Lastly, big data and analytics enable advanced applications of Industry 4.0 since the system's intelligence depends on big data and analytics (Frank et al., 2019).

Past research shows an affirmative relationship between the perceived gain of using the technology over the competition (relative advantage) and the adoption of information system innovations [Oh et al. 2019]. Relative advantage is the degree to which an innovation is perceived as being better than the idea it supersedes [Rogers 2003]. Business processes like resource planning are expected to change with the adoption of IoT (Zhang et al., 2015). Performance measurement using statistical learnings for infrastructure will change with the adoption of IoT (Archetti et al., 2015).

2b. IoT Solutions Adoption Factors

b.1. Well researched topics

b.1.1. Trust – Inter-Organizational & Institutional

B2B (Business to Business) transactions are between private, government, and not-for-profit organizations and many individuals within them. Compared to B2C (Business to Customer), the average transaction size is of higher value; evaluation is extensive and more private, sometimes even involving multiple negotiations. Terms of transactions and data about such businesses are seldom available in public. The Decision-making process in the Organization may involve multiple functions and different individuals at various levels. (Gary Lilien & Rajdeep Garewal, 2012, Handbook of B2B Marketing).

"B2B transactions are often quite complex, involve very high stakes, and incorporate great risk or fear, uncertainty, and doubt. Despite the 'left brain' quantitative analysis that goes into a B2B buy, customers like working with suppliers they trust" (Gary Lilien & Rajdeep Garewal, 2012, Handbook of B2B Marketing). Innovative products or solutions introduced into the B2B market sometimes have such diverse applications that market opportunity cannot be imagined entirely at the outset (Mohr et al., 2010). Technological innovations can result in existing products/platforms' obsolescence (Govindarajan & Kopalle, 2006). Customers have high fear, uncertainty, and doubt over adoption, resulting in hesitancy to buy or implement (Dhebar, 1996). Besides technological obsolescence uncertainty, customers may face concerns about the reliability of the new technology's performance and vendors' ability to deliver and provide promised products and services (Mohr et al., 2010).

Trust plays an essential role in customers taking the leap of faith when adopting new technologies. Trust is a belief that the partner will fulfil the obligations and behave to serve the firm's needs and long-term interests (Scheer and Stern, 1992). In an organizational setting, trust is between two specific parties: a trusting party(trustor) and a party to be trusted(trustee) (Driscoll, 1978, Scott C.L., 1980, Mayer & Davis, 1995). Inter-organizational trust simultaneously operates at multiple levels: interpersonal trust (between the buyer agent and seller's salesperson), personal trust in the opposite firm, and inter-firm trust between companies (Fang et al., 2008). Interpersonal trust refers to the extent of trust between individuals interacting with counterparts in a partner organization, whereas inter-organizational trust is the extent of collectively held trust placed towards partner organizations by the focal organization's members (Zaheer et al., 1998).

Interorganizational trust, compared to interpersonal trust, has a greater influence on performance, negotiation, and conflict. Inter-organizational and interpersonal trust are related but theoretically distinct. Interpersonal trust affects inter-organizational trust. The higher one trusts the supplier's point of contact, the more one's Organization trusts the supplier organization. No support was found for interpersonal trust with the cost of negotiations, level of conflict, or performance (Zaheer et al., 1998). Hence, inter-organizational trust is considered an independent variable over interpersonal trust for adopting IoTS subscriptions in the B2B capital goods market.

IoTS, including equipment diagnostic technologies, are in a nascent stage of development for the commercial B2B industry, with few exceptions, like the airline industry. OEMs (Original Equipment Manufacturers) and service providers are developing technologies for individual industry segments as the needs are sometimes specific to an individual factory level or a process within a factory. Companies have scarce or no resources to develop or evaluate these new technologies. Companies rely on the past performance record of the OEM / service provider. Companies will check on the experience of other users with the provider's expertise and their reliability in keeping their promises. Such experiences based on personal, or referrals create trust in the provider's competence to perform the task effectively.

Technological innovation often brings in new players due to its radical new performance attributes. Newer players are flexible in resource allocation and tend to be more successful as the incumbents are too slow, routinized, and uninterested in developing disruptive technologies (Christensen, 1997, Henderson, 1993). However, new entrants have a lower level of inter-organizational trust as they do not enjoy the relationship that an incumbent can create due to long-term business association (Chandy & Tellis, 2000, Obal Michael, 2013). Subsequent research has found that incumbents, on occasion, have been successful as they have pre-existing relationships (Obal Michael, 2013).

By attribute, technological innovation means something new where the risk is high due to information asymmetry, outcome uncertainty, and risk aversion, whether from a new supplier or an incumbent. During this early stage of adoption of innovative technology, relationship or contracts are insufficient to build trust due to limited knowledge and uncertainty about the future dynamics (Mayer & Argyres, 2004, Bachman & Inkpen, 2011). In such a case, external legal arrangements or certification system that provide a reliable structural safeguard would create confidence in the company during the early adoption stage of new contracts (Bachman & Inkpen, 2011). When the trustor and trustee do not know each other or have a trust deficit in a partner, a third actor functioning as a 'third party guarantor' play a vital role in trust creation. The external institution creates a perception for the buyer of a third-party mechanism that can facilitate a successful transaction. Institutional trust is vital in an impersonal economic environment where familiarity and similarity do not exist (Ratnasingam et al., 2005).

Inter-organizational and environmental contexts play an essential role in influencing new technologies adoption (Kuan & Chau 2001). Inter-organizational factors like trust between trading companies are essential in adopting new technologies. The behavioural intention behind adopting new technology is significantly influenced by perceived relative advantage, ease of use, compatibility, competence, and integrity (Lin, H. F., 2011), where perceived relative advantage, ease of use, and compatibility are innovation attributes. In contrast, competence and integrity are the attributes of trust. Understanding technology characteristics and trust are crucial in determining the behavioural intention of new technologies (Wu, L., & Chen, J. L., 2005). Trust is enforced when organizations develop shared goals, form social-relational embeddedness, and initiate influence strategies. Inter-organizational trust leads to better inter-organizational collaboration and knowledge sharing (Chen, Y. H., Lin, T. P., & Yen, D. C., 2014).

In an inter-organizational context, information and knowledge sharing strengthens the connectedness and alleviates the dysfunctional conflicts between the partners built upon the positive relational benefits (Cheng, J. H., 2011). A relationship can help marketers manage service more efficiently and customer lifetime value (CLV) more effectively (Rust & Chung 2006). The firm and the customer receive additional value from the relationship, such as convenience, timesaving, reduced prices, simplified information processing, buying and consuming, reduced perceived risks, and maintaining a state of psychological comfort (Sheth & Parvatiyar 2000; Verma et al. 2016). Further, if the intangible intensity increases, the customer will find it challenging to develop alternate suppliers against an incumbent supplier with a multiplex relationship. To adopt new technologies, it is critical that the customers are engaged early and integrated as a key collaborative partner with the provider or manufacturer and have close and intensive relationships (Kiel, Arnold & Voigt, 2017). To increase customer sales and reduce sales volatility, multiple levels of ties like R&D and market alliances create relationship multiplexity that is rare and difficult to imitate, strengthen the supplier-customer relationship (Tuli et al., 2010).

In inter-organizational exchanges, complex explicit contracts or vertical integration substitutes trust (Granovetter, 1985; Bernheim & Whinston, 1998; Bradach and Eccles, 1989; Dyer and Singh, 1998; Gulati, 1995). Formal contracts undermine trust, and encourage opportunistic behavior, signalling distrust in the exchange partner (Ghoshal & Moran, 1996, Macaulay, 1963, Fehr and Gachter, 2000). Adopting new technologies brings uncertainties not present in doing business with established products, as observed during online transactions and business in the digital market. The buyer's trust in the seller depends on the level of perceived risk. Third-party institutional mechanisms engender trust not only in reputable sellers but the entire community of sellers (Pavlou, P. A., & Gefen, D., 2004). Institutional structures may include legal regulations, professional codes of conduct that may or may not be legally binding, standards, and other formal and informal norms of behavior, reducing the risk of lost trust. Where institutional trust exists, both parties refer to institutional safeguards in their decisions and actions and can thus develop trust without prior personal experience in dealing with one another (Bachmann & Inkpen, 1986). Institutional-based trust institutions can be considered functionally equivalent to a personal third-party guarantor (Bachmann & Zaheer 2008).

b.1.2. Leadership - Top Management commitment & IT expert on the Board

There is a paucity of studies on social, behavioral, economic, and managerial aspects of the IoT as it is relatively recent. Companies find it challenging to make informed decisions regarding adoption (Lee & Lee, 2015). Customers' preparedness to adopt new technologies depends on their readiness to support technology and their inclination to engage with new technologies (Zhu et al., 2003). Employees' technical competence, training, and development to adopt new technologies define the firm's technological competence [Curran 2017]. Companies with higher technological competence are more likely to accept new technologies [Zhu et al. 2002].

Research has indicated that the strategic benefit of new tools is often poorly communicated by the top management and decision-makers, resulting in resistance to change, even if the new technologies help enhance productivity (Knight, 2015). Financial resources are crucial for acquiring new technologies, training, and supporting the people, and buying or upgrading equipment, technology, and infrastructure. Difficult decisions are required to get the financial resources beyond the operational needs for investment in new technologies (Griliches 1990). The decision-makers increasingly face competing investment demands with limited resources (Kabir et al., 2014). Organizational support is a significant variable for introducing any new technology and running it successfully (Oh et al. 2019).

Top management could influence new technology adoption positively by articulating a vision and reinforcing the value to the organization [Ramdani et al., 2009]. They should update the organization's strategy and promote and communicate support for innovations that improve its core mission and vision (Baker 2012; Tushman & Nadler 1986). The firm's top managers play a vital role in obtaining resources and planning implementation where the top management is passionate, innovative, welcoming new technologies, and prepared to take risks (Grover, 1999). Top management commitment and support are essential during implementation when coordination across organizational divisions and conflict resolution are critical [Sila 2013]. The role of decision-makers in promoting innovation within an organization is crucial and depends on their cognitive skills, knowledge about their organization, knowledge about their customers' needs, and new technologies (Bartel & Lichtenberg 1987; Bartel et al. 2007, Brynjolfsson & Hitt 1996). The presence of an expert with an information technology background in a senior leadership position like on the Board would meet such requirements.

The conundrum of prioritization of investments can be eased if the investments for adopting IoT solutions are reduced or newer business models like subscription models are introduced. Technology development drives down costs (Porter and Millar, 1985; Porter and Heppelmann, 2015). The cost of sensors used in IoT enabling the machine-to-machine communication has reduced over time (Maintenance Assistant Website, 2016, Rymaszewska, Helo & Gunasekaran (2017). Improving performance and lowering costs for providing high-quality services or products is key to increasing profits and reputations of industrial factories. Information about different aspects of the factory can be obtained through the data collected. The data helps understand the operating conditions and detect faults and failures, which is an important topic for research (Sung (2018).

Innovations seldom happen by chance, sustained innovation even less so. (Drucker, 1993). Some organizations successfully bring in innovative products, e.g., Apple, Dyson, GE, 3M, P&G, Alphabet (Google), Amazon, Tesla, and Samsung, to name a few. Some characteristics distinguish innovative organizations from less innovative firms in the same industry (Subramanian et al., 1996). Characteristics like risk tolerance, communication flexibility, and willingness to share knowledge differentiate innovative organizations (Egbu et al., 1998). A 'no blame' culture stimulates employees to develop and experiment with new ideas (Dulaimi et al., 2002).

Besides in-house R&D, companies should seek external knowledge for innovation activities (Cohen and Levinthal, 1990). Director's heuristics and knowledge influence strategic decision-making (Day & Lord, 1992). Directors' innovation experience has solid specificity based on their knowledge and work experience (Mcdonald et al., 2008). Innovation-experienced Directors can address short-sighted behavior and motivate the company to commit to investments in innovation for long-term sustainable development. They can manage the conflict between management's view on short-term goals and the shareholder's goal for long-term value and investment returns (Fama & Jensen, 1983).

The Board's role is to nurture and spark behaviors that deliver innovative solutions ahead of the competition. The Board needs understanding and expertise on the nature of successful innovation (Knox, 2002). Directors with experience in technology are more likely to make R&D investments (Custodio et al., 2019). Directors' willingness and ability to take risk-taking increase and they are more likely to support investments in innovation (Barrosocastro et al., 2017). Innovation output significantly increases when companies appoint individuals with innovation experience on their boards (Boh et al., 2020). Directors with innovation experience bring in knowledge of potential external partners in and outside the industry, enabling the company to pull resources from the innovation ecosystem and influencing innovation performance (Daft et al., 1988). Innovation experience of the Director grants legitimacy in carrying out innovation activity. During the innovation implementation phase, they can help ease resource and knowledge

b.1.3. Organization culture

Organizational culture is its people's shared values, beliefs, and practices providing norms of expected behavior (Schein, 1985, 1996). Organizational culture defines its identity, the values important for its daily business, the expectations set for individuals, and the practices they will follow. Organizations that value innovation empowers people to think unconventionally, propose new ideas or ways of doing business without the hindrance of rigid structure, and take measured risks. 3M and P&G have developed a culture of innovation where employees are encouraged to experiment and champion innovations and not be afraid to disagree with managers in pursuit of ideas (Sutton, 2001).

An innovative culture motivates new solutions and improvements. It has mechanisms for feedback and communication, allowing for autonomous work, initiating innovative products, and a rewards and incentive system. (Hartmann, 2006). An innovative culture is organization-specific and differs between organizations as the degree of elements comprising innovative culture will vary, innovative mission & vision statements, democratic communication, safe spaces, flexibility, collaboration, boundary spanning, incentives, and leadership. (Dombrowski et al., 2007).

Weakness in innovative organizational culture results in a disarray of innovation projects and ineffective execution (Dombrowski et al., 2007). Implementing new products, services, or processes is a big challenge in an ever-changing world (Gann, 2000). Rapid changes result in the obsolescence of knowledge and require the Organization and its people to constantly learn and adapt to new structures, processes, tools, and strategies (Lemon & Sahota, 2004).

An organization culture that values and facilitates calculated risk-taking, willingness to change the status quo, incentivizes and rewards accomplishments and efforts, inter-function cooperation, openness, flexibility, and internal communication are crucial to support norms for innovation and the firm's financial and market performance (Hogan & Coote, 2014).

The Greek philosopher Heraclitus said: "The only constant in life is change," and per Plato, "Heraclitus, I believe, says that all things pass, and nothing stays and comparing existing things to the flow of a river, he says you could not step twice into the same river." Change is moving from the present to a future state (George and Jones, 1996).

Organizations and their people have to go through a change when adopting new technologies, processes, or systems. Per (Rashid et al., 2004), organizational culture and attitude to change are associated. People are the most critical factor affecting the change and are the most difficult to deal with (Linstone & Mitroff, 1994). The people's attitude in the Organization is challenging to change once they have been learned (Dunham, 1984). Resistance to change can be due to any factors or a combination of – the risk of failure, reduction in economic security, fear of job change, psychological threats, and lowering status (Dawson, 1994). Three types of attitudes - affective (linked to being satisfied or anxious), cognitive (linked to usefulness & necessity for change and knowledge to make the change), and behavioral (intention) are attributes of attitude to change (Dunham et al., 1989). A key obstacle to change is "fear of the unknown" or "unfamiliar situation" it is better to address the cognitive attitude first as a person may be more receptive to change once he/she has the information and knowledge about a potential change be made. Addressing cognitive attitudes will require clear communication from the leadership (Rashid et al., 2004). Their research further concludes that people are more receptive to change when organizational culture is dedicated to its mission and goals, quick to respond to environmental changes, and unwilling to accept poor performance.

Organizational culture should be aligned with the strategy of the Organization as the managerial actions will be driven through it (Hartmann, 2006). He also mentions that the strategic orientation of firms determines managerial actions suitable to create a culture that motivates innovative behavior. Many changes and transformation programs fail to deliver the intended results with which they were started. This is often due to many programs concurrently thrust on the employees or budgets cut or waning of top management commitment leading to employees becoming cynical when new mission-vision statements are announced (Dombrowski et al., 2007).

b.2. Emerging research topics

b.2.1. Interoperability

Companies face challenges regarding the capacity and performance of the collected data volume, and the market has various platforms to select from. IoT platform is defined as a foundational infrastructure to enable connectivity between things, securely and storing data to be used intelligently (Moura et al., 2018). Many IoT platforms in the market are seldom interconnected (Schneider, Jacoby, et al., 2020). IoT platforms offer proprietary interfaces and protocols (Bröring et al., 2018). The European project Unify-IoT found more than three hundred IoT platforms, and each of these platforms promotes its own IoT infrastructure, proprietary protocols, API (application programming interfaces), and formats. Incompatibility between different IoT platforms arises due to diverse operating systems (OS), programming languages, data structure, and application development. It is costly for companies to manage heterogeneous interfaces on distinct platforms (Noura et al., 2019). Hence the need for the platforms to work together, i.e., interoperability. IEEE defines interoperability as "the ability of two or more systems or components to exchange information and to use the information that has been exchanged" (Radatz J, Geraci A, Katki F, 1990). Due to interoperability and fragmented platform solutions, entry barriers prevent the emergence of IoT ecosystems (Bröring et al., 2017).

Industry 4.0 requires cyber-physical systems (CPS), big data, AI, IoT, and its associated technologies to connect numerous devices to optimize industrial productivity, comprehensibility, and accountability (Khanna and Kaur, 2019). Communication of data sensed from heterogeneous devices, processing and transmitting filtered information for monitoring and control is the primary objective of the Industrial IoT, also called IIoT. Such monitoring and control improve machine lifetime performance, reduce operational cost and improve the working condition of personnel. (Vrana, 2020). Companies face challenges in terms of the volume of data collected (thousands of terabytes of data per second for processing and analysis), and the market has various platforms for processing such data to select from.

IoT platform is defined as a foundational infrastructure to enable connectivity between things, securely and storing data to be used intelligently (Moura et al., 2018). Many IoT platforms available in the market are seldom interconnected (Schneider, Jacoby, et al., 2018). IoT platforms offer proprietary interfaces and protocols (Bröring et al., 2018). The European project Unify-IoT found more than three hundred IoT platforms, and each of these platforms promotes its own IoT infrastructure, proprietary protocols, API (application programming interfaces), and formats. Incompatibility between different IoT platforms arises due to diverse operating systems (OS), programming languages, data structure, and application development. Due to Interoperability and fragmented platform solutions, entry barriers prevent the emergence of IoT ecosystems (Bröring et al., 2017). It is costly for companies to manage heterogeneous interfaces on distinct platforms (Noura et al., 2019). Hence the need for the platforms to work together and for Interoperability. Interoperability enables standard communication between a heterogeneous set of devices with different protocols, operating systems, and software and applications from different vendors, cloud, and fog/edge service providers with different architectures (Sinche et al., 2019). Interoperable platforms can directly translate users' unstructured data into a standard industrial format to allow the dynamic exchange of useful information (Hazra et al., 2021).

Interoperability taxonomy

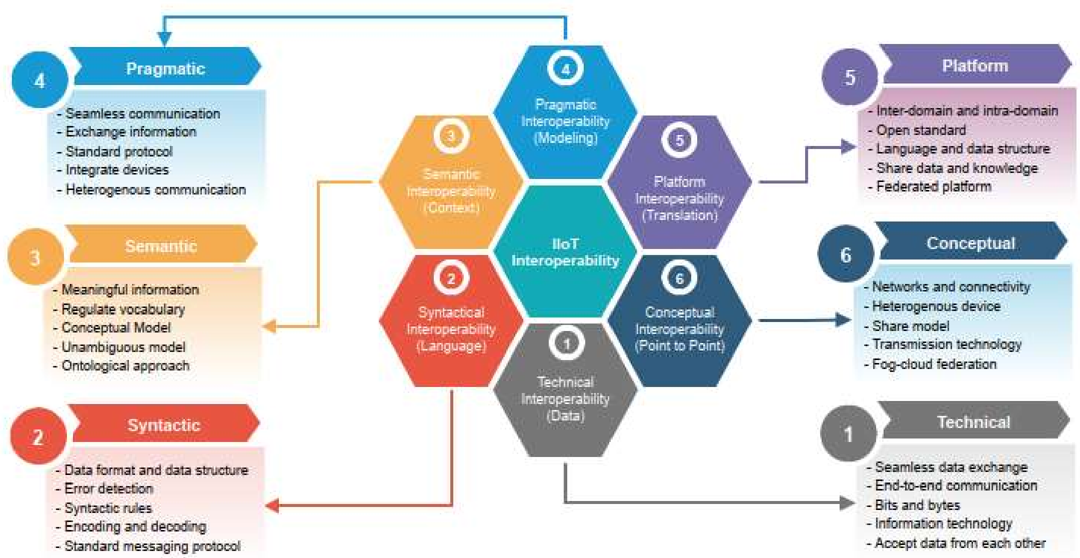
In the literature, Interoperability has been classified into different levels of Interoperability.

i. European Telecommunications Standards Institute (ETSI) classifies four levels of Interoperability in their framework – Organizational, Semantic, Syntactic, and technical Interoperability (Der veer & Wiles, 2018).

ii. LCIM – Levels of Conceptual Interoperability Model framework determine the possibility of Interoperability between systems at an early or conceptual stage and categorize it into six levels from no interoperability to full Interoperability – No interoperability (level 0), Technical Interoperability (Level 1), Syntactic Interoperability (Level 2), Semantic Interoperability (Level 3), Pragmatic Interoperability (Level 4), Dynamic Interoperability (Level 5), and Conceptual Interoperability (Level 6) to design an interoperable system. (Tolk & Muguira, 2003).

Figure 3

Interoperability Taxonomy – Tolk and Muguira(2003), Hazra et al., (2021)



➢ The European Interoperability Framework (EIF) identifies three levels of Interoperability [IDABC: European Interoperability Framework for Pan-European eGovernment Services, Luxembourg (2004)]: Organizational Interoperability, Technical Interoperability, and Semantic Interoperability.

- IDEAS project developed a framework based on ECMA/NIST Toaster Model, ISO 19101, and ISO 19119 and augmented through the Quality Attributes (IDEAS, 2003). "Interoperability is achieved on multiple levels: inter-enterprise coordination, business process integration, semantic application integration, syntactical application integration, and physical integration."
- C4ISR, Architecture Working Group (AWG), developed LISI (levels of information systems interoperability) in March 1998 for the US Department of Defense (DoD) as a maturity model to identify Interoperability. A critical element of interoperability assurance is a clear prescription of the common suite of requisite capabilities inherent to all information systems that desire to interoperate at a selected level of complexity.
- E-health interoperability framework - developed by NEHTA (National E-Health Transition Authority) initiatives in Australia comprising -
    - Organizational Interoperability creates cohesion amongst approaches to governance, finance, legislation, and business processes.
    - Information interoperability owns the family of information building blocks from basic data type elements to terminologies.
    - Technical Interoperability combines all aspects of standards along with the broad architectural approach linking e-health services and information.

Through their research, Ford et al., 2007, identified sixty-four different types of Interoperability mentioned in research papers, government control documents, reports, or standards. These different types of Interoperability can be vastly segmented into technical or non-technical. Classification of Interoperability, though some of the interoperabilities classifications between technical and non-technical, can be subject to interpretation or the lens used to review it based on the application.

Table 1

Interoperability Classification

Technical	Non-Technical
Communications	Organizational
Electronic	Operational
Application	Process
Database	Cultural

Types of Interoperability

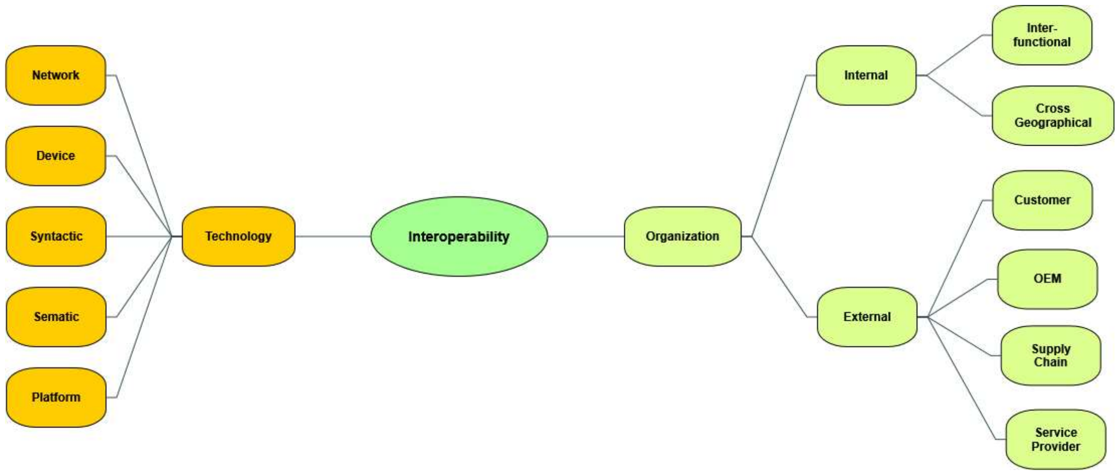
For this study, I consider two major interoperability impacting IoT subscription adoption in the B2B capital goods market - Technical and Organizational Interoperability.

Interoperability of equipment or capital goods is technically required for data collection from sensors, transmitting, processing, and gaining meaningful insight to take action. It covers hardware and software interoperability by connecting devices, systems, and services through interfaces and protocols. Information exchange should have the same meaning when processed by any computer, system, or human.

Information and intelligence created technically are not only required for the safe and optimum running of equipment; it is also linked to business goals, inter-functional collaboration, decision-making authority, and allocation of resources. For holistic benefit, intra- and inter-organizational interoperability are required to be effective and useful. Organizations are networked with their suppliers, service providers, and customers, i.e., external partners, and at the same time, they are networked within different functions for quick and accurate processing of information for decision-making.

Figure 4

Types of Interoperability



Organizational Interoperability – Businesses cannot run in isolation. It is networked internally for cross-functional exchange of information and externally with suppliers, service providers, and customers. Organizational Interoperability occurs when business processes, responsibilities, and expectations are aligned to meet agreed and mutually beneficial goals. Organizational Interoperability aims to meet the user community's requirements by making services available, easily identifiable, accessible, and user focused. (IDABC: European Interoperability Framework for Pan-European eGovernment Services, Luxembourg (2004)).

- **External -** Organizations must communicate and transact with other companies based on shared business references, standards, or norms. These agreed references avoid redefining cooperation rules, increasing efficiencies, and faster information processing. Organizational Interoperability aligns participating companies' goals and business processes and makes easily identifiable, accessible, and user-focused services available. (Chen 2003, European initiatives to develop Interoperability).
- **Internal** –. Business processes must be thoroughly documented, including defining authority and decision-making responsibilities. The organization may need to redesign and implement changes to integrate and align systems for relevant information

exchange. The information enabled through IoT services is not limited to usage in the equipment operation alone but is also required for planning, procurement, inventory control, cash flow management, and the organization's performance.

Technical Interoperability - incorporates both software and hardware interoperability. It enables exchanging information between devices and servers through a network in a comprehensible, unambiguous, and meaningful way. It encompasses –

- Device Interoperability – is concerned with
  - the exchange of information between heterogeneous devices and heterogenous communication protocols
  - the ability to integrate new devices into any IoT platform.

  The proliferation of devices without universally accepted standards results in different communication technologies being used, affecting Interoperability for multiple devices working at a user's location. Devices may have varying computational capabilities built-in, including - processor speeds, RAM, communication, technology, and battery life, depending on the manufacturer's design resulting in interoperability constraints.

- **Network Interoperability –** concerned with mechanisms to enable seamless message exchange between systems through different networks for end-to-end communication. IoT devices generally rely on short-range wireless communication and network technologies intermittently. Network interoperability deals with issues such as addressing, routing, resource optimization, security, and mobility support (Bello et al., 2017)
- **Syntactical Interoperability –** concerned with the interoperation of the format and the data structure used in any exchanged information or service between heterogeneous IoT

system entities. Syntactic interoperability problem arises when senders' encoding rules are incompatible with the receivers' decoding rules, leading to mismatching messages.

- **Semantic Interoperability** – It is the ability of computer systems to exchange data with unambiguous, shared meaning**.** It is concerned with enabling different agents, services, and applications to exchange information, data, and knowledge meaningfully. [W3C, BW3C Semantic Integration & Interoperability Using RDF and OWL.]. It ensures that the meaning of exchanged information between any computer system and/or human remains the same.
- **Platform interoperability –** concerned with interoperability issues due to the availability of diverse operating systems (OS's), programming languages, data structures, architectures, and access mechanisms for things and data. It also encompasses interdomain and intradomain Interoperability concerned with systems and organizations' ability to exchange information among different domains like different industries, markets, or even geographies. This non-uniformity restricts application developers from developing cross-platform and cross-domain IoT applications.

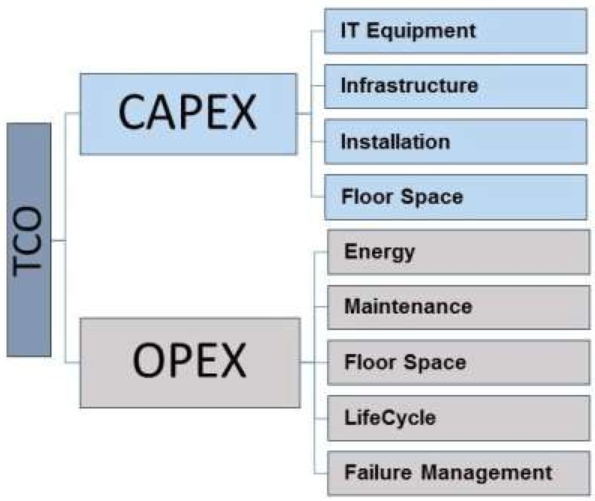
b.2.2. Implementation Cost

Industries are focused on economic efficiency, as every penny counts. The resources are scarce, and one of the key elements that the firms consider is the costs required when making investment decisions from the various available projects. IoT Solutions require enhanced computation, storage, and networking infrastructure. The current ratio between IT capacity and its related costs is already high, and further capacity increase due to IoT Solutions implementation will impose further cost additions on a firm (Mahloo et al., 2017).

The total cost of ownership (TCO) of a private cloud implementation can be up to 80% less expensive than public cloud options over five years and nearly 90% less than a traditional server approach (Analysts, T. G. M., 2014). A TCO model for a typical data centre lifecycle is proposed considering all major cost categories from deployment to the operational phase (Mahloo et al., 2017).

Figure 5

Total Cost of Ownership (TCO) model of private cloud implementation



Note: Mahloo, M., Soares, J. M., & Roozbeh, A. (2017, September).

Implementing IOT Solutions will have similar cost elements to some extent. Besides the hardware and infrastructure costs, it will additionally have

- Software costs, including license, customization, and modification for compatibility
- Hardware costs, including the sensors, routers, gateways, servers, storage capacity
- Data and system integration costs from different software/platforms
- Services costs include external consulting fees, training of employees, insurance, and cloud service.
- Operating Costs like subscription fees, maintenance costs

b.2.3. Vendor lock-in

Vendor Lock-in is when a customer using a product or service cannot easily transition to a competitor's product or service. The cost of switching to another vendor is so high that the customer is essentially stuck with the original vendor. Vendor lock-in is usually the result of proprietary technologies incompatible with competitors.

Switching costs bind customers to suppliers making it difficult for them to change and giving suppliers market power to make higher profits. It further discourages competitors from breaking into one another's customers (Farrell & Klpemperer, 2007). The position of a supplier to bind customers through switching costs is a marketing strategy as it creates a barrier to entry for the competition (Porter, 1980). Suppliers provide bargains to early adopters to gain market acceptance and increase prices for the late adopters as collective switching costs become high (Farrell, 1997). Firms use technological incompatibility as a strategic tool to lock in customers and reap benefits through aftermarket business (Marionoso, 2001)

A firm with more existing customers will be less aggressive in seeking new customers. Switching costs for existing customers discourage them from adopting alternate products or components, making it harder for competing/entering firms to gain business. It encourages the entering firms to serve the unattached ones (Farrell & Shapiro, 1989).

Lock-in of technologies as a result of a high rate of adoption has been investigated. The pervasive adoption of technology, even if it is by chance, lockout others even if it is inferior (Arthur, 1989). For example, the US nuclear-reactor technology during 1950~60’s was dominated by light water reactors even though the research showed that gas-cooled reactors were technologically far superior. US Steam vs. petrol car competition in the 1890s and the QWERTY typewriter keyboard are other historical cases where pervasive technology adoption locked in, and the customer's choice was limited.

In some markets, switching costs, there is a natural product/firm life cycle. Adoption of new products is gained through unattached buyers by providing better quality or attractive prices. Later the product attracts new customers to a point where the firm will rely on established buyers. In the final phase, the firm will serve the locked-in buyers as the product would have lost its attractiveness to unattached buyers. The locked-in buyers will either perish or make new product-specific investments, and the firm/product loses its customer base (Farrell & Shapiro, 1988).

Besides the switching costs, especially in the industrial B2B capital goods market, the set-up cost is a significant factor too for vendor lock-in. The set-up costs to adopt new products can be high, involving high asset acquisition costs, installing, and commissioning costs. The removal and disposal costs and efforts are also high. This allows the seller to increase aftermarket prices and have high-profit margins by keeping the prices just below the total replacement cost of an alternate supplied product (Farrell & Klemperer, 2007).

Technology skill, complexity, data security, and customization have no significant influence on the intention to adopt, whereas vendor lock-in significantly influences the intention to adopt cloud-based ERP (Martins et al., 2014). On the contrary, switching costs alone do not form an entry barrier. Switching costs create a negative correlation between the existing market share and the share of a new placement (Farrell & Shapiro, 1988).

Past research looks at switching costs and set-up costs as major factors in creating a vendor lock-in for the user and vendor lock-in as an entry barrier as part of a marketing strategy. The adoption of technology creates a lock-in for technology, limiting the options that the user can have. Past papers also look at the challenges users face in lock-in conditions and the product cycle the sellers go through with switching cost impact. However, there is a gap in the current literature on vendor lock-in as an antecedent to adopting new technology.

b.2.4. Analytic Intelligence

As a multidisciplinary concept, analytics is defined as the means to acquire data from diverse sources, process them to elicit meaningful patterns and insights, and distribute the results to proper stakeholders (Soltanpoor & Sellis, 2016). Analytics is further classified based on the intelligence it provides - *Descriptive analytics* is focused on the past. It summarizes the data and produces information from a diverse set of heterogeneous data (Delen & Demirkan, 2013). *Predictive analytics*, on the other hand, is forecasting analytics and is concerned with the future. *Prescriptive analytics* is concerned with recommendation and guidance and provides organizations with adaptive, automated, and time-dependent sequences of operational actions. It answers questions like “What should be done?” and “Why should it be done?” (Delen & Demirkan, 2013).

Descriptive Analytics is the “data summarization” phase and reports the past. It answers the question “What has happened?” and extracts information from raw data. There is also an extension to descriptive analytics named “diagnostic analytics,” which reports the past but tries to answer the questions like “Why did it happen?”. It helps organizations in grasping the reasons for the events that happened in the past. Diagnostic analytics allows enterprises to understand relationships among different kinds of data.

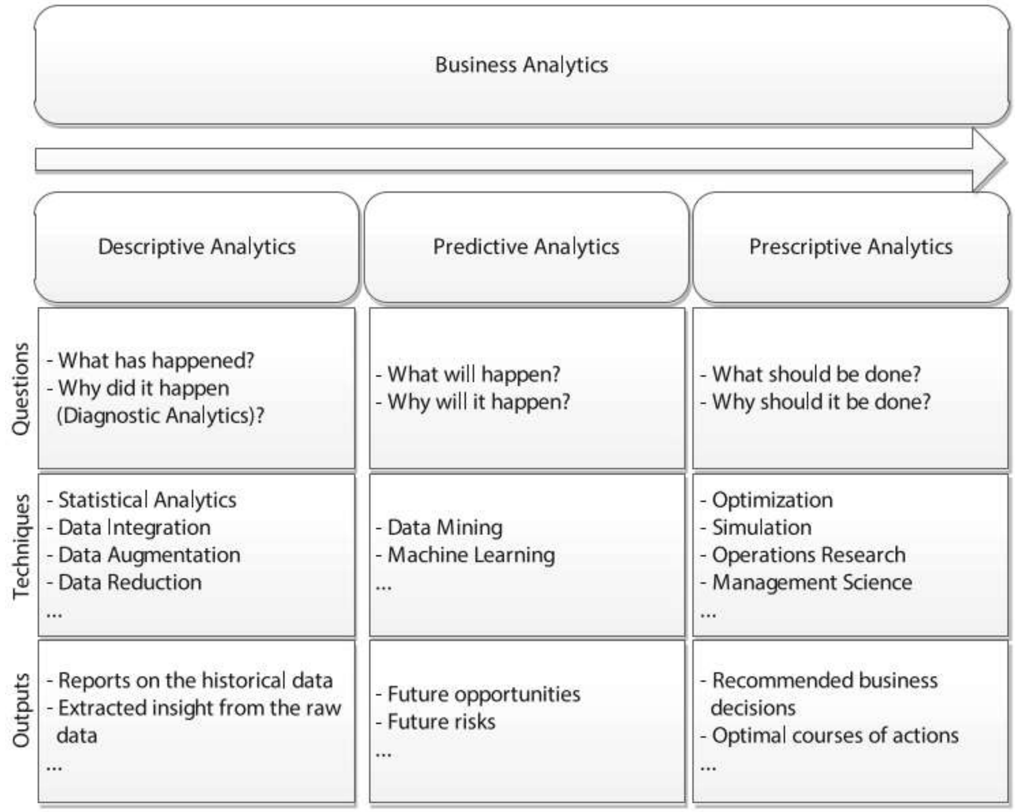
Predictive Analytics - Predictive analytics is a business intelligence (BI) technology that uncovers relationships and patterns within large volumes of data that can be used to predict behavior and events. Unlike other BI technologies, predictive analytics is forward-looking, using past events to anticipate the future. (Wayne W. Eckersen, 2007). It is the “forecasting or extrapolation” phase and incorporates the descriptive analytics output, machine learning (ML) algorithms, and simulation techniques to build accurate models that predict the future. It answers the questions “What will happen?” and “Why will it happen?” in the future?” (Delen & Demirkan, 2013). The output of predictive analytics is multiple predictions and their equivalent probability scores.

Both descriptive and predictive analytics assist organizations in extracting proper insights from the data they own.

Prescriptive Analytics - is predictive analytics that prescribes one or more courses of action and shows the likely outcome/influence of each action. It answers the questions “What should I do?” and “Why should I do it?”. (Haas et al., 2011). It is purely built on the “what-if” scenarios phase and provides enterprises with adaptive, automated, time-dependent, and optimal decisions (A Basu, 2013). Prescriptive analytics considers the output of predictive analytics with compliance rules and business constraints to generate the best courses of action as the optimal decision. The main elements of prescriptive analytics are optimization, simulation, and evaluation methods (Bertsimas & Kallus, 2020). Prescriptive analytics systems generally have two important characteristics: (1) They provide the enterprise with actionable outcomes. These outputs generate comprehensible prescriptions in terms of actions. (2) they support feedback mechanisms for tracking the suggested recommendations and unprecedented events occurring in the system’s lifetime. (Soltaanpur & Sellis, 2016)

Figure 6

Analytics Stages



Note: Soltanpoor, R., & Sellis, T. (2016, September).

Intelligence is based on the principle of difficult-problem-solving-abilities (Iantovics et al., 2018). There is no standardization of intelligence measuring, and there are multiple definitions, especially for machine intelligence, including computational intelligence, machine intelligence, and intelligent systems. Alan Turing, 1950 presented the definition of machine intelligence - a computing system was considered intelligent if a human assessor could not decide the system's nature as human or artificial based on questions asked from a hidden room. The definition is based on the idea of an artificial cognitive system that can imitate the intellect of a human being. Later tests found that the "intelligent computer program" surpassed average human Intelligence by 100 on some tests (Sanghi & Dowe, 2003).

Knowledge is the collection of skills and information acquired through experience or instructions from others. Intelligence is the ability to apply knowledge systematically and reliably. Intelligence enables the use of knowledge to be transferred from one context to another. (Marcus, 2020). Information relates to raw, unverified, and unevaluated data gathered from numerous sources, while intelligence refers to processed, evaluated, and perspective-driven data gathered from trusted sources.

Intelligence provided by IoT solutions is its computational ability to obtain improvements for various difficulties. It should enable selection of the most appropriate systems based on Intelligence (Iantovics, 2021).

- **Diagnostics** /descriptive analytics are conducted after an event has occurred. It is a reactive decision-making process and cannot prevent downtime or associated costs. It assists in root cause analysis and determining the relationship between the cause and effect. Equipment fault diagnostics is a procedure of mapping measurement information received as data from instruments on the machine to the types of faults. It recognizes patterns from the data or signals requiring highly skilled and trained people with expertise in a specific area of application (Jardine, Lin & Banjevic, 2006).
- **Prognostic**/prescriptive analytics provide Intelligence to detect incipient failures and forecast remaining useful life (R.U.L.). Prognostic intelligence predicts the time remaining before a failure can occur depending on the existing condition compared with the history of failures. Such intelligence helps the operation and maintenance team plan for corrective actions in advance and reduce costly shutdowns or catastrophic failures.

Asset maintenance is an important but non-core/non-productive activity for the customer. It has direct costs associated with hiring and training the maintenance staff and indirect costs due to unplanned maintenance and failures leading to reduction or stoppage of production and non-optimal spare parts inventory. The diagnostic analysis will help reduce failure or unscheduled maintenance needs, which are more expensive than predictive or preventive maintenance (Wu et al., 2017; Lee et al., 2014, Zhang et al., 2013). Some of the equipment in the manufacturing plant can be specialized, where in-house skills are not available, requiring external expertise. Customers need solutions providers or manufacturers who can take on such responsibility and provide diagnostic and prognostic feedback for optimizing the equipment's health.

Diagnostic analytics helps detect imminent failures, whereas prognostic analysis predicts the component's R.U.L. (remaining useful life) (Daniyan, Mpofu, Adeodu, 2020). MTBR (Mean time between repair) and MTTF (mean time between failure) can be predicted using mathematical or stochastic models based on the data collected in real-time and available historical data (Jian et al., 2017, Bui, 2015).

Prognostic Analytics uses the acquired data to train for fault detection, prediction, and decision-making (Maio and Zio, 2013, Liu et al., 2018, Frosini et al., 2014, Islam et al., 2017, Daniyan et al., 2020). IoT-enabled data acquired from sensors on the asset is diagnosed, assessed, and used to predict the health of the asset components, thereby enabling rectification work prior to failure or degradation of its performance. P.H.M. (prognostic and health management) system uses real-time and historical data to provide actionable information to the customer, enabling them to make intelligent decisions for improved performance, safety, reliability, and maintainability (Vogl, Weiss, Helu, 2019). Customers can focus on their core production-related work by adopting IoT solutions that can provide diagnostic and prognostic Intelligence to act upon such that their operational needs are not sacrificed.

IoTS technologies enable data and information interaction remotely. Traditional laborious processes can be optimized through remote access to data, thereby improving productivity and reducing production time. Virtualization can simulate an act before it occurs in reality (Hurst, Shone, and Tully, 2019). Other indirect improvements that improve the customer's productivity are reducing the downtime of assets, improving the quality of the product manufactured, the safety of the people, and the operations, reducing wastage, and improving efficiency.

IoTS technologies are evolving, including C.P.S. (cyber-physical systems) and DT (Digital Twin). A CPS system integrates the physical assets using the data from sensors mounted or embedded in cyberspace to process data and feed results back to solve real-world problems. The information exchange is autonomous, intelligent, and can make decisions and take action (Tan et al., 2019).

Industrial companies are under intense competitive pressure and shorter innovation cycles (Schuh et al., 2017). IoTS enables companies to focus on customers' desired outcomes, built to meet specific needs with a value proposition to improve performance continuously using insights collected (Schuh et al., 2020).

b.2.5. Asset Criticality

Asset criticality is the relative risk of a high cost arising from the failure of that asset. So criticality is the relative risk of an asset from a cost perspective, calculated to understand which assets deserve attention and money to prevent failure. To understand this definition of asset criticality, we need to understand its parts: (1) failure mode, (2) cost, (3) risk, and (4) relative importance. (Criticality: A Key Idea in Asset Management - By Trilogics Technologies, Inc. 2005)

Assets - ISO 55000 (International Organization for Standardization) defines **assets** as an item, a thing, or an entity with potential or actual value to an organization. For my study, I will focus on the physical / tangible assets of the organization (equipment, inventory, and properties).

Criticality is the measure of risk associated with an asset. There are two main attributes in the analysis of criticality: Frequency of failure of the asset and severity of the consequence of a hypothetical failure (Javier, S. P., Márquez, A. C., & Rosique, A. S., 2016).

Criticality = Frequency of Failure * Consequence of Failure

Failure - There are two ways of describing the failure mechanism. The first assumes that failure depends only on the condition variables, which reflect the actual fault level, and the predetermined boundary. In this case, the most commonly used failure definition is simple: failure occurs when the fault reaches a predetermined level. The second builds a model for the failure mechanism using historical data available. A failure can be defined as the event that the machine is operating at an unsatisfactory level, or it can be a functional failure when the machine cannot perform its intended function at all, or it can be just a breakdown when the machine stops operating. Similar to diagnosis, the approaches to prognosis fall into three main categories: statistical approaches, artificial intelligent approaches, and model-based approaches. (A.K.S. Jardine et al. / Mechanical Systems and Signal Processing 20 (2006) 1483–1510)

b.2.6. Responsiveness

An organization's responsiveness to meet customers' requirements and expectations has been researched mostly from the quality of service, trust, relationship, and perception building. The impact of responsiveness on modern-day businesses involving E-service, online retailing, financial services, and shopping sites is of keen interest to the researchers.

Responsiveness represents the service provider’s ability to respond quickly to requests and suggestions and assist customers in case of problems (Zeithaml et al.,2000). Customers have identified a fast response as an element of high-quality service (Voss, 2000), but in practice, many companies fail on this dimension (Kaynama & Black, 2000). Here, responsiveness is defined as the extent to which customer feedback is considered and the promptness of reply. Since responsiveness reflects customers' perceptions of the service provider's ability and willingness to respond to customer needs, it is also expected to impact trust. (Gummerus et al., 2004).

Responsiveness is considered part of the total service offering from the supplier's perspective. Responsive firms can adapt to changes in customer needs, be more efficient and save customers' time, help improve customer performance and enjoy higher profitability (Theoharakis & Hooley, 2003). However, information is a vital input required for firms to be responsive. A positive relationship between information & responsiveness and between responsiveness and firm performance is established through a case study on Bose (Daugherty et al., 1995).

A responsive supplier reduces uncertainty and creates a positive customer perception, creating trust (Gumerus et al., 2004). Responsiveness is one of the five dimensions used to measure customer perception of service quality by the SERVQUAL instrument proposed by Parasuraman, Zeithaml, and Berry, 1988. For e-services and digital businesses, the service quality measuring instrument was modified to an 8-dimension scale, including responsiveness by Li and Suomi, 2009. In digital businesses, flexibility and responsiveness are the important value drivers identified. The value of IT systems depends on the employees and their responsiveness (Lapierre, 2000)

In the business-to-business (B2B) markets, customers need individual treatment, speedy delivery, and an enhanced level of responsiveness. Responsiveness is crucial for building relationships as it shows a firm's respect towards customers' valuable resource: time (Gro¨nroos, C., 1997 & 1999). Responsiveness is a causal link between organizational resources and firm performance (Theoharakis & Hooley, 2003).

Past researchers have looked at responsiveness as a factor in creating trust, building relationships, creating positive perceptions, impacting firms' performance, and creating instruments to measure it as a factor for service quality. There is a paucity of research on the impact of the responsiveness of firms in industrial B2B environments. To what extent does a responsive supplier affect the customer's decision to rely on digital solutions for their assets/equipment/machinery? Will the customer consider risking mission-critical assets dependent on inputs from a responsive supplier, or would the customer test it on non-critical assets to build confidence before applying the digital solutions to the critical equipment?

2c. Summary of Review

Technology adoption can fail if the perceived technology lacks direction [Lawrence 1997]. Business models and their implications have been studied from the aspect of strategies moving from being product-centric to bundle of products and services; however, it had neglected the role of technologies such as engine health management in servitization or P-S bundles (Lightfoot, Baines, and Smart, 2013 and Luoto, Brax, and Kohtamäki, 2017). Possibilities arising from the collection and using the data are being explored by manufacturing companies to complement the P-S bundle (Grubic & Jennions, 2018). The evolution of IoT technologies like sensors, gateways, and wireless technologies are in a hyper-accelerated innovation cycle and cannot enjoy the benefits of having universally accepted standards, privacy and security issues, and thus the proliferation of poorly tested devices (Lee & Lee, 2015). IoT's characteristics of networked solutions become more challenging as an error or mistake can bring down the entire network, depending on its type, and cause a disorder. Accordingly, most prior literature focuses on the technological aspects, challenges, opportunities, categorization, and applications. The adoption of new technology in a firm depends on inter-organizational and environmental factors besides the characteristics of technology alone (Kuan & Chau, 2001). Past literature has deeply delved into factors involving trust, leadership, and Organization culture.

Divergent factors from firms' perspectives in adopting new technologies like managerial, organizational, technological, environmental, and individual require deeper examination (Ghobakhloo et al. 2011b). Maturity models for implementation (e.g., Schuh et al., 2017; Lee et al., 2015; Lu and Weng, 2018; Mittal et al., 2018), the impact of implementation on industrial performance (Dalenogare et al., 2018) are recent studies to bridge the gap. Management research on this subject is limited (Brettel et al., 2014). Also, most studies are case study based and lack empirical evidence on adopting these technologies in manufacturing companies (Frank et al., 2019).

For decades, industrial markets have been using ICA – instrumentation, control, and automation to improve operational performance. They have skilled people, experience, and financial strength to invest in IoT Solutions. Still, IoT Solutions are deployed as proof of concepts or small pilot projects. The adoption rate in an all-pervasive way is yet to happen. Factors like interoperability have been researched from the perspectives of taxonomy, technology, and organization needs. Vendor lock-in has been studied from an economic view of switching costs and set-up costs. The adoption of new technologies leading to vendor lock-in has been studied; however, the effect of vendor lock-in on adopting new technology requires investigation. The cost of implementing new solutions similarly needs investigation. Past research on the total cost of ownership from the Datacentre perspective or Cloud solutions perspective is similar to this study. However, how the implementation cost affects the adoption of IoT solutions is yet to be investigated. There is also a gap in the literature on identifying how the user decides which type of equipment they would implement new IoT Solutions in their operation. Past literature reviews the criticality of equipment and how to identify which equipment in a particular operation is critical depending on the frequency of failure and the financial implication of the failure. However, there is a gap in the literature to test whether critical assets in operation would be the first to adopt new technologies like IoT Solutions. For industrial businesses responsiveness of a vendor is important. Customers want their product manufacturing to continue unhindered. Any downtime is a potential loss of revenue. Vendors' responsiveness to maintaining the equipment in an operational mode, reliably, and at optimum levels is crucial. Past research has linked responsiveness to building trust, creating a positive perception of the vendor, and firm performance; however, whether the customer will consider implementing new technology like IoT Solutions for their critical assets depends on the vendor's responsiveness investigated.

This study is an effort to bridge the gaps identified and contribute to the scientific knowledge of subscription of IoT Solutions for capital goods/physical assets in the B2B market as it has the potential to one day enable subscription of capital goods for their outcome or performance across the industry and not some specific cases as in today's world. This study will validate the perspective on the adoption of IoT Solutions for capital goods and identify drivers for transition into such new business models, and will be able to address the research questions -

1. What are the drivers affecting the adoption of IoT Solutions in the B2B capital goods market to transition from deployment to adoption stage in the process of technological innovation?
2. Are B2B users with the capability of Instrumentation, Controls, and Automation (ICA) find value from analytic intelligence provided by IoT Solutions a reason for its adoption?
3. Are any causal links affecting the relationship between the drivers for adopting IoT Solutions?

3. Research model and Hypotheses

3.1 Proposition I

IoT platform is a foundational infrastructure that securely connects things(devices) and stores data to be used intelligently (Moura et al., 2018). Many IoT platforms available in the market are seldom interconnected (Schneider, Jacoby, et al., 2018). IoT platforms offer proprietary interfaces and protocols (Bröring et al., 2018). The European project Unify-IoT found more than three hundred IoT platforms, and each of these platforms promotes its own IoT infrastructure, proprietary protocols, API (application programming interfaces), and formats. Incompatibility between different IoT platforms arises due to diverse operating systems (OS), programming languages, data structure, and application development. Analysts such as Gartner and AMR estimate that companies use 30% ~ 40% of their IT budget on custom application integration projects due to a lack of Interoperability. It is costly for companies to manage heterogeneous interfaces on distinct platforms and more so for small companies. Application developers get constrained due to the limitation of cross-platform implementation (Noura et al., 2019). Additionally, it will require people to be trained and skilled on multiple platforms. Hence the need for the Interoperability of platforms to work together to reduce the cost of integration, development, and management costs for implementing IoT Solutions.

- Companies (OEMs - Original Equipment suppliers) have domain knowledge and expertise on the products or equipment they supply. However, these pieces of equipment, also called capital goods, are just a small part of many types of assets that the customer needs to operate and maintain their operations. Traditionally the customers will deploy IACS (Industrial automation and control systems) to collect and monitor the data on operating parameters of the capital goods installed for safe, secure, and reliable operation of an Industrial process (IEC 62443 — International

Electrotechnical Commission - International Standards on an industrial communication network, IT security for networks and systems). The IACS were mainly separated from the ICT (information and communications technology) environment, connecting the data into a wider network. Firewalls and zoned architecture are used where the connectivity of IACS is required to protect the core control system. IoTS adoption in the IACS environment requires architectural changes and better connectivity (Boyes et al., 2018).

- Physical assets, also called objects, become things of IoT when they have a unique identifier, an embedded system, and the ability to transfer data over a network (Wigmore Ivy, IoT Agenda, 2014). Objects become Smart when they can understand and react to their environment. Smart objects thus have the attribute of being digitally augmented with sensing, processing, being connected, and being autonomous (Kortuem et al., 2009). The Smart objects of the physical world are interconnected through the Internet to create a global network. Hyper-innovation in IoT has seen the development of many platforms, devices, and solutions in the recent past. Each solution has its own IoT infrastructure, API's and data formats making it difficult, if not impossible, for cross-platform access, application development, and plugging in devices into heterogeneous IoT platforms (Noura et al., 2019). Besides, there is no reference standard for IoT platform technology available, and efforts from various communities are underway, eg. European community under ICT-30, IEEE P2413 working group on the standard for an architectural framework for the IoT (Aloi et al., 2017).

Users need an interoperable platform that can exchange data across platforms of individual equipment and understand it; IoT devices can be plugged in irrespective of the platform, integrating different communication standards and radio interfaces (Aloi et al., 2017). The ability for multiple platforms from different vendors to work together seamlessly will enable data exchange across the platform, improving overall intelligence for the customer at a plant level. It will enable the customer to accurately identify the root cause of abnormal conditions and take corrective actions as required. The equipment's abnormal condition may be due to the process/environment in which it works rather than the equipment's operation itself. Accurate identification of root cause due to interoperability of the platform help user directly address the problem area leading to lesser downtimes, higher productivity, and safer working of its staff. It will also help reduce the overall cost of adopting IoT solutions.

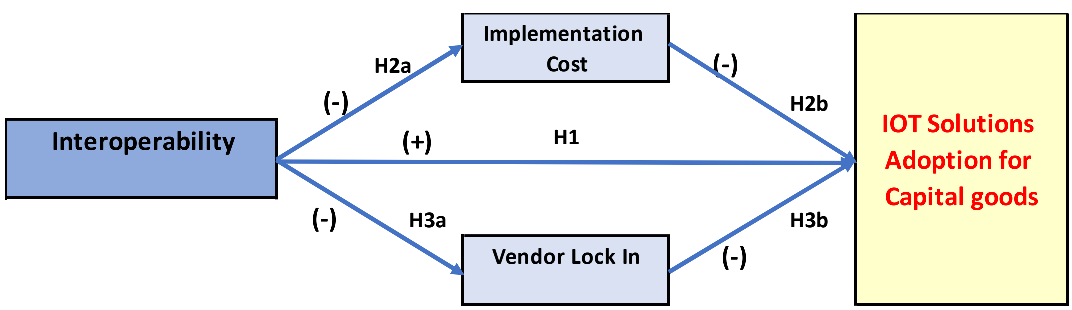
Objects become Smart when they can understand and react to their environment. Physical assets, also called objects, become things of IoT when they have a unique identifier, an embedded system, and the ability to transfer data over a network (Wigmore Ivy, IoT Agenda, 2014). Smart objects thus have the attribute of being digitally augmented with sensing, processing, being connected, and being autonomous (Kortuem et al., 2009). An organization has multiple assets from different OEMs with sensors and actuators installed to make the equipment smart. Each device type may be different in processing capability functionality and based on different technology, causing problems with understandability during data processing and transmission. For reliable and smooth operations, semantic Interoperability for extreme heterogeneity of devices, networks, and platforms will provide unambiguous data transfer, which is not open to more than one interpretation.

The Smart objects of the physical world are interconnected through the Internet to create a global network. Hyper-innovation in IoT has seen the development of many platforms, devices, and solutions in the recent past. Each solution has its own IoT infrastructure, API's and data formats making it difficult, if not impossible, for cross-platform access, application development, and plugging in devices into heterogeneous IoT platforms (Noura et al., 2019). Besides, there is no reference standard for IoT platform technology available, and efforts from various communities are underway, e.g. European community under ICT-30, IEEE P2413 working group on the standard for an architectural framework for the IoT (Aloi et al., 2017). Due to Interoperability and fragmented platform solutions, entry barriers prevent the emergence of IoT ecosystems (Bröring et al., 2017). Proprietary solutions by the vendors on its applications and difficulty in plugging non-interoperable IoT devise into different IoT platforms are barriers of entry for other vendors and risks for the customer. Un-interoperable communication between vendors and non-standardized platform architecture pushes end-users to rely on the specific vendor for their plant operations, creating a barrier for other vendors (Hazra et al., 2021). Platform Interoperability will reduce the risk of vendor lock-in due to such proprietary solutions by allowing open-source solutions and fair competition.

Hence, the hypothesis:

Figure 7

Interoperability Framework



H1 –Interoperability positively and directly impacts the adoption of IoT Solutions.

H2 – Implementation cost of IoT Solutions mediates the relationship between interoperability and adoption of IoT Solutions.

H2a – Interoperability has a negative impact on the implementation costs of IoT Solutions.

H2b — Lower the cost of implementing IoT Solutions, the adoption of IoT solutions will be higher.

H3 – Vendor Lock-in effect from proprietary IoT Solutions mediates the relationship between interoperability and adoption of IoT Solutions

H3a - Interoperability has a negative effect on the vendor lock-in from proprietary IoT Solutions

H3b – Lower the vendor lock-in effect of proprietary solutions, the higher will be the adoption of IoT solutions

3.2 Proposition II

ISO 55000 (International Organization for Standardization) defines assets as an item, a thing, or an entity that has potential or actual value to an organization. These include physical assets (equipment, inventory, and properties) and non-physical assets (financial assets, IP, licenses, brands, reputation, or agreements). For the topic of study, I will refer to physical assets as assets. Assets, by definition, are of value to an organization and are needed to meet customers' demands. Assets have a life cycle – from idea development to replacement or destruction. It becomes imperative to manage and optimize the cost of assets over their lifecycle and reduce business risk as they are essential to the organization's profitability (Bandur, K. M., Katicic, L., & Dulcic, Z., 2015). However, not all assets are equally important in the process or operation. Some are more critical depending on their role in achieving the organization's goals, and others are less in relation to other assets. Certain assets may be critical in one location or part of the process but less critical in another.

Criticality is the measure of risk associated with an asset (SWEFC). It helps to identify which asset needs a priority in terms of attention and money to prevent failure, as criticality controls the cost side of asset management. There are two main attributes in the analysis of criticality: Frequency of failure of the asset and severity of the consequence of a hypothetical failure (Javier, S. P., Márquez, A. C., & Rosique, A. S., 2016).

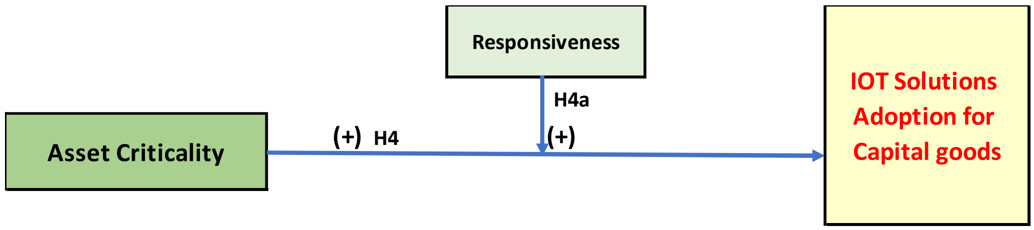
Criticality = Frequency of Failure * Consequence of Failure

Companies intend to operate the plant to its full design capacity or even more to maximize the profits or sometimes survive against competition. For the plants to operate at peak load conditions for an extended period requires high reliability from all critical assets (Muganyi, P., Mbohwa, C., & Madanhire, I., 2018). Companies aim to decrease the operating costs, which from an asset's perspective means low life cycle cost, higher overall equipment effectiveness, high reliability, and lower maintenance costs. Besides the loss of production, the non-optimal performance of critical assets can result in quality defects, financial losses due to delays, customer complaints, and unplanned expenses on spare parts (Bousdekis et al., 2018). Approximately 60% of all manufacturing equipment fails prematurely after implementing corrective maintenance actions (Karim, Candell & Soderholm, 2009).

As part of O&M strategies (Operation and maintenance), maintenance and reliability strategies have evolved and are shifting towards using new technologies. From reactive (run to failure) to static time-based maintenance, companies are looking at predictive maintenance capabilities through advanced information on the health of the assets based on the operating parameters collected and processed on a real-time or exception basis. Predictive analysis enables companies to reduce risks, make intelligent decisions and create a differentiated customer experience. IoT technologies such as sensors and wireless connectivity have enabled real-time predictive analytics and the offering of IoT solutions (IoTS) to meet specific customer requirements, such as enabling proactive decision-making based on the predictive analytics recommendation for a specific critical asset in a particular working environment. The optimal performance of critical assets could thus be met, reducing the risks of financial losses, product quality, and people safety. Hence, the hypothesis:

Figure 8

Asset Criticality Framework



H4: The criticality of an asset in an organization's operations positively influences the adoption of IoT Solutions.

H4a: Responsiveness of IoT Solution provider strengthen the relationship between asset criticality and adoption of IoT Solution

3.3 Proposition III

The activity of asset maintenance is an important but non-core/non-productive activity for the customer. It has direct costs associated with hiring and training the maintenance staff, indirect costs due to unplanned maintenance and failures leading to reduced or stopped production, and non-optimal spare parts inventory. The diagnostic analysis will help reduce failure or unscheduled maintenance needs, which are more expensive than predictive or preventive maintenance (Wu et al., 2017; Lee et al., 2014, Zhang et al., 2013). Some of the equipment in the manufacturing plant can be specialized, where in-house skills are not available, requiring external expertise. Customers need solutions providers or manufacturers who can take on such responsibility and provide diagnostic and prognostic feedback for optimizing the equipment's health.

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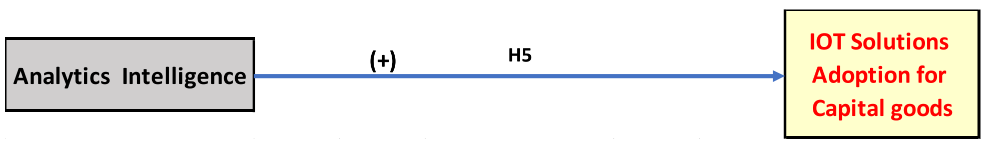
Industrial companies are under intense competitive pressure and shorter innovation cycles (Schuh et al., 2017). IoTS enables companies to focus on customers' desired outcomes, built to meet specific needs with a value proposition to improve performance continuously using insights collected (Schuh et al., 2020). Hence, the hypothesis:

Figure 9

Analytics Framework



H5: Analytic Intelligence positively impacts the adoption of IoTS solutions.

4. Research Method & Data Collection

4.1 Introduction

The following section presents the exploratory sequential design mixed-method research as the research methodology. The approach aligns with the definition of mixed-method research, involving collecting and analyzing data, integrating the findings, and drawing reasoning from qualitative and quantitative methods in a single study (Tashakkori & Creswell, 2007). The qualitative method will provide insights for proposing/building the hypotheses. Integrating it with the quantitative method will test the hypotheses for their acceptance or rejection (Caruth, 2013, Cronholm & Hjalmarsson, 2011).

The author observed the reluctance of users to shift from IACS (Industrial automation and control systems), which has been used industry-wide for a few decades and take the leap of faith to adopt IoTS when working in the field. During his professional work, the author made these observations involving capital goods business in the B2B market, primarily in the process plants like midstream O&G, downstream petrochemical, and fertilizers plants.

4.1a Qualitative Method

Extant literature on this subject is reviewed from various perspectives, including the topics of adoption of innovation, subscription and lease, service-dominant logic, servitization, value, risk and security, ecosystem, customer experience, competitive advantage, life cycle costs, Industry 4.0, IoT, IIoT, asset criticality, Organization culture, behavior, platform interoperability, diagnostic and prognostic intelligence, responsiveness, vendor lock-in, and trust. Multiple literature sources, including peer-reviewed articles from journals, practitioner-oriented articles in the business press, handbooks, reports by consultants, and market research firms, are used for the review. Based on the observations and literature review, variables affecting the adoption of IoTS subscriptions are identified, and a conceptual framework is created.

Interviews with subject matter experts (SME's) are conducted to exclude erroneous personal biases and beliefs and gain insights into the research topic. A semi-structured interview approach is taken to keep the interviewees focused on the key issues and, at the same time, open-ended enough to get additional insights consistent with the nature of the study and prioritize the most impactful ones based on their experiences. To get diverse and holistic views, eighteen senior industry leaders, decision-makers, influencers, or subject matter experts (SMEs) were contacted to participate in the interviews. The qualification criteria for identifying the target interviewees are business leaders with relevant experience in the B2B business of capital goods as a user or provider/supplier and familiar with IoT technologies and solutions offerings. This specific research focuses on IoT Solutions in the B2B capital goods market; the interviewees should have experience and insights into the capital goods business and IoTS. The interviews are designed to collect perspectives from the three distinct entities engaged in such business transactions – the OEMs, the solution providers, and the users. Ten interviews have been conducted based on the interviewees' availability and interest in participating from May 2021 to July 2021. The profile of the interviewees is provided in Table 2.

The interviews were conducted virtually using Zoom due to restrictions imposed by the Covid pandemic. Each interview is about one to one & a half hours long and is recorded and transcribed. Each interviewee was provided with a set of questions prior to the interview. It was to make them aware of the topic of discussion and have their thoughts together. Open-ended questions were used during the interview to get additional insights. Appendix A has a repository of questions used during the interviews. Analysis of the findings from the interviews as the primary data source helped in triangulation with researchers' observations, literature review, and other documents. Based on the findings from the interviews, the framework is refined and presented in figure 1.

4.1b Qualitative Data Collection:

The research method involved human participants (SMU 2020). As part of qualitative research, interviews with subject matter experts were conducted. The CITI program (Collaborative Institutional Training Initiative) encompassing conflicts of interests and Institutional responsibilities affecting investigators was completed, and the IRB application, including the questionnaire to be used for the semi-structured interviews, was approved by Institutional Review Board (IRB) prior to collection of data from interviews as it involved human interactions. The list of questions approved by IRB is enclosed in Appendix A.

Interviews with subject matter experts (SMEs) were conducted. To get diverse and holistic views, SMEs were selected based on their experience in the B2B capital goods market with an orientation towards IoT or implementation of innovation in B2B organizations. They were suppliers, service providers, or users to get the views from all segments involved in B2B transactions of capital goods and IoT solutions implementation. Eighteen senior industry leaders, decision-makers, influencers, or subject matter experts (SMEs) were contacted to participate in the interviews, of which ten consented. Table 2 provides the list of interviewees' profiles, industry segments, and the geographical location where they were based.

No sensitive information about the firms and survey respondents was captured or disclose in any form.

Table 2

Interviewee's profile – Qualitative Data collection

No	Industry Type	Designation	Country	Type
1	Material Handling	Sr. Vice President, APAC (Sales & Service)	Singapore	OEM
2	Heavy Eqpt Mfg - Engines	Managing Director	USA	OEM
3	Heavy Eqpt Mfg - Construction	Managing Director (South Asia & India)	India	OEM
4	O&G	Chief of Engineering, MNC Conglomerate including O&G, Petrochemical, Telecom	India	User
5	Ammonia / Fertilizer	Vice President, Projects	Indonesia	User
6	O&G	Sr Lead Engineering, Instrumentation	Canada	User
7	Information & Tech	CTO - Strategic Solutions, IOT & Embedded Systems Practice	India	Service Provider
8	Information & Tech	Digital Officer & Global Head - Mfg Industry Vertical	India	Service Provider
9	Aerospace, Defense, Security, Transportation	CVO (Chief Value Officer) - Digital - Monetization - Value - Pricing - Subscription - Agent of Disruption - Author - Speaker	USA	Service Provider
10	Aviation Services (MRO Business)	Dy CEO / COO	Singapore	Service Provider

4.1c Qualitative Data Analyses-

Interviews from the SMEs (subject matter experts) were conducted remotely using Zoom and recorded. These interviews were then transcripts, and highlights from the interviews were reviewed. NVivo version 12 software was used to code the interviews to identify the first-order concepts. From these first-order concepts, second-order themes were developed to validate the independent variables having a relationship and an impact on the dependent variable of IoT Solution subscription of the capital goods in the B2B market. Prelim data from interviews showed ninety-seven constructs that the interviewees mentioned during the discussion. Word frequency was mapped on the transcripts from interviews.

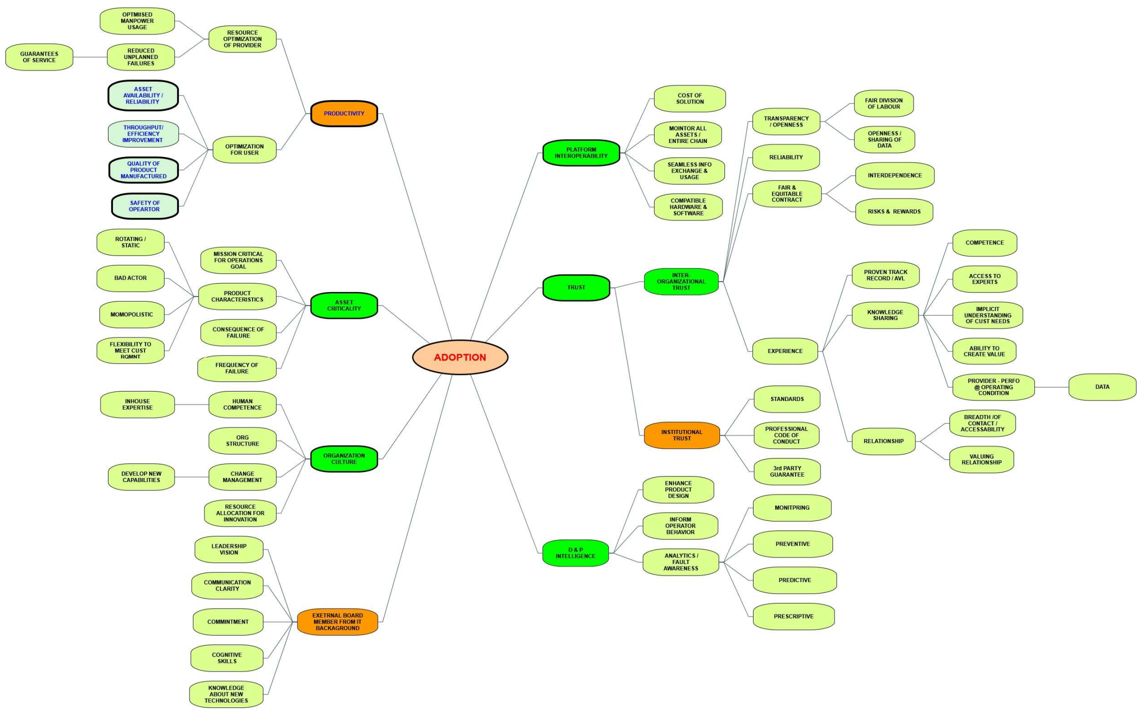
Figure 10

Word Cloud Map

Based on word frequency, ninety-seven constructs were mapped using NVivo 12 software per the below concept map.

Figure 11

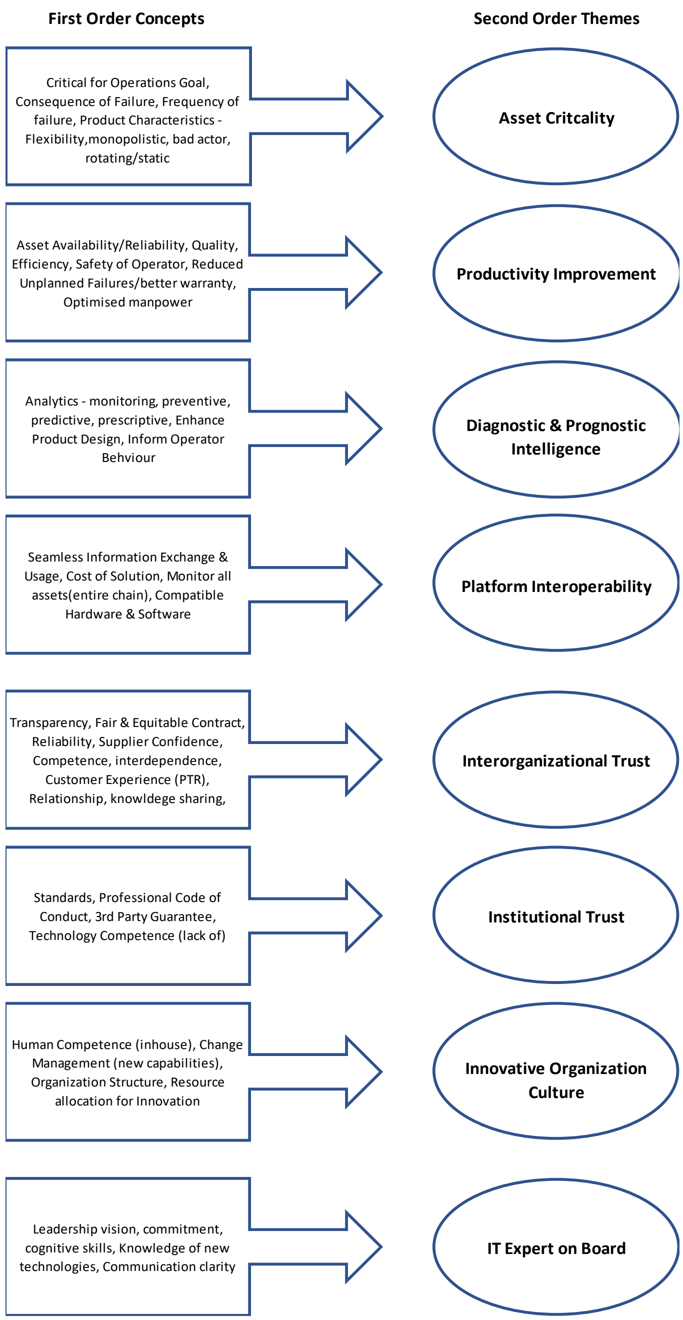
IoT Solution adoption concept map



A concept map was used to drill down to more fundamental constructs for creating the first-order concepts and developing second-order themes.

Figure 12

Interview based Second Order theme



4.2 Quantitative Method

Based on the conceptual framework and qualitative data analyses a survey instrument is developed to test the hypotheses quantitatively. Scale for the measure of responsiveness and adoption of innovative solutions, i.e., IoT Solutions, is adopted from prior research. New measures for interoperability, asset criticality, analytics intelligence, implementation cost, and vendor lock-in are developed systematically by defining the construct, pretesting the questions, administering the survey, testing reliability, and assessing the validity. The survey questionnaire is pretested. Responses from sixteen respondents were checked for the correctness of the instructions, readability and effectiveness of capturing the research intent. The questionnaire was then administered to a larger audience using Qualtrics online survey platform. Two screening questions were used to eliminate respondents who did not consent to the survey and those without experience with IoT.

Additionally, for the accuracy of responses, the online Qualtrics platform had filters to remove responses from speeders, bots and duplicate submissions. For speeders, a time limit of three mins as a minimum was set for completing the responses. Any response completed in less than 3 mins was removed from the survey. The time limit was kept at more than 1/3rd of the median time required by sixteen respondents during the pretest survey. Accordingly, 89 responses were removed from the data points to be taken for analysis.

Bot detection using ReCaptchascore filters responses that would likely be bots. It uses Google's invisible ReCaptcha technology requiring no interaction with the respondent or blocking them; however, it is flagged, and if the captcha score is less than 0.7, the response is removed from the data for analysis. 11 such responses that were flagged, are removed. Finally, duplicate responses are removed from the survey. Multiple submissions are flagged if the respondent uses the same browser to attempt the survey multiple times. Six such submissions are removed from the data points to be taken for analysis.

The target respondents are people working in B2B Industrial companies and service providers from technology companies. The respondents are C-Suite, managers and senior engineers from operations/maintenance/ reliability/procurement/projects/supply chain / Information and operation technology functions who know IoT Solutions in an Industrial context.

The survey was administered to get responses from major industrial Asian countries, China, India, Japan, and ASEAN (Singapore, Indonesia, Malaysia, Philippines, Brunei), besides the USA, which is a global leader in investments in the field of IoT. For a better response rate and accuracy of the responses, the survey was translated into Japanese and Chinese and administered in the native language to respondents from their respective countries. The accuracy of the translation into Japanese and Chinese language was validated through a review from natives of China and Japan. For the respondents from the rest of the countries, the survey was administered in the English language.

Table 3 *Geographical Response Frequency*

	Freq	%
USA	23	12%
China	40	21%
Japan	62	32%
India	38	20%
ASEAN	31	16%
Total	194	100%
Malaysia	2	6%
Indonesia	2	6%
Singapore	23	74%
Brunei	2	6%
Philippines	2	6%
ASEAN Total	31	100%

A total of 697 surveys were sent out, from which 194 complete and clean responses were collected for further analysis at a response rate of 27.8%. The surveys were sent out in mid July 2022 and the responses were collected and survey closed in mid Aug, 2022.

Table 4 *Survey Response Rate*

Survey Response Rate	Qualtrics	Direct	Total
Total Respondents	646	51	697
Good Responses	161	33	194
% good responses	24.92%	64.71%	27.83%

4.2a Instrument

A seven-point Likert scale survey questionnaire is used to collect the data to test the hypotheses quantitatively basis the framework. A seven-point Likert scale best captures the sentiments of the respondent and provides better accuracy. Miller (1956) argued that the human mind has a span of absolute judgment that can distinguish about seven distinct categories, implying that the ability to make judgments distinguishing categories is limited to seven. It suggests that any increase in the number of response categories beyond six or seven might be futile. Indices of reliability, validity, and discriminating power had poor ratings on two-point, three-point, and four-point scales and significantly better for scales with response categories up to seven-scale (Preston, C. C., & Colman, A. M., 2000).

The questionnaire was developed and refined basis (a) the framework created after the subject matter experts' semi-structured interview and (b) original instruments used in other studies. Further, the survey form was pretested with a sample of 10% of the targeted responses.

Validity and reliability tests on the constructs are conducted basis of the responses from the sample survey. The questionnaire did not need any change as the new constructs of interoperability, asset criticality, analytics intelligence, implementation costs, and vendor lock-in indicated adequate internal consistency.

4.2b Model Building and Estimation

The Structural Equation Model (SEM) is used to build and estimate the model. In SEM, the relationship between the independent variables of Interoperability, Asset criticality and Analytic intelligence, the mediating variables of Implementation cost and vendor lock-in and the moderating variable of responsiveness are assessed by estimating regression coefficients of latent variables regressing on the dependent variable – IoT Solutions Adoption. SEM is used to effectively measure the latent variables that cannot be measured directly. The factors used for measurement of the latent variable are tested for their reliability and validity using Confirmatory Factor Analysis (CFA). Each Independent variable relationship with the dependent variable is assessed as a separate model. I have used the Stata/BE17 (release 17) statistical software package to run the CFA and SEM analysis.

4.2c Measures

Following previous research methods, I follow a two-stage analytical procedure, wherein the first stage includes a confirmatory factor analysis to examine the measurement model and its robustness. In the second stage, relationship analysis between the dependent, independent, mediating, and moderating variables is done to establish the relationship (Anderson & Gerbing 1988). The reliability and validity of the items measuring the construct are tested to assess the robustness of the measurement model.

4.2c.1 Construct Robustness -

- **Reliability** is the consistency of the measure and checking whether the results from the tests are reproducible under consistent conditions (Carlson Neil et al., 2009). Internal consistency indicates the degree to which items within a construct measure different feature of the same concept, i.e., factors on the test are related to all the other factors and measure the same entity (Hajjar, 2018).

Further uni-dimensionality check is done by examining average inter-item correlations to test that all items are interrelated. As per the guideline, the average inter-item correlation should be in the range of 0.15 to 0.5. However, the average inter-item correlation can average within the guideline range by averaging many low coefficients with high ones. Hence the range and distribution of the correlations are examined. The average inter-item correlations should be moderate in magnitude and should cluster narrowly around the mean value. (Clark & Watson, 1995).

- **Validity** originates from the Latin word 'Validus,' meaning strong. The instrument's validity is the degree to which it measures what it intends to measure. Two types of validity tests are conducted to check the robustness of the measurement model - Convergent and Discriminant (divergent) validity.
- **Convergent validity** is the extent to which different items used to measure the hypothesized construct measure the same concept. AVE and CR are used to test the convergent validity.
- The **- average variance extracted** (AVE) is the ratio of construct variance to the total variance. It evaluates the amount of variance captured by a set of items on a scale relative to measurement error (Netemeyer R. et al., 2003).
- **Composite reliability** is a measure of internal consistency in scale items similar to Cronbach's alpha. It is the total amount of true score variance to the total scale score variance (Fornell & Lacker, 1981, Netemeyer R. et al., 2003).

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum Var\ (\varepsilon_i)}$$

Where

i. λi= completely standardized loading for the ith indicator,

ii. Var (ε_i) = variance of the error term for the ith indicator, estimated based on the value of standardized loading => $\varepsilon_i = 1 - \lambda i^2$

- **Discriminant validity** is the test to examine the measure of constructs that are not supposed to be related are unrelated (not correlated) (Hajjar, 2018).

In order to establish the reliability and validity of the items used to measure the constructs, the following measures are used –

- Cronbach's alpha: an acceptable value > 0.7 (Nunnally, 1978)
- Average inter-item correlation: cluster narrowly around the mean, an acceptable value > 0.30
- Convergent Validity –Average variance extracted (AVE): an acceptable value > 0.5 indicate convergent validity. (Fornell & Larcker, 1981)
- Composite Reliability (CR): an acceptable value > 0.7 (Hair et al, 1998)
- Discriminant Validity: an acceptable value> √AVE > interitem correlation (Fornell & Larcker, 1981)

4.2c.2 Model Testing

The model is tested according to the instrument's reliability and validity tests. SEM (structural equation modelling is used to test and evaluate multivariate causal relationships between the variables. Goodness of Fit and statistical significance testing is done for the model.

- **Goodness of Fit-**

A Goodness of fit is used to assess whether the specified model fits the data. Over the years, statisticians have developed and suggested many indices to test various aspects of the model. However, I will only use it to guide and examine the model with significance tests. I will assess my model on the following-

- **Absolute fit indices** measure how well the model fits the sample data.
    - Chi-square (χ^2) assesses the magnitude of discrepancy between the sample and fitted covariance matrices (Hu and Bentler, 1992). However, where the sample size is small, a Chi-square (χ^2) statistic lacks power, due to which it may not be able to discriminate between a good or poor-fitting model (Kenny & McCoach, 2003). In my case, the sample size of less than 200 is considered small; accordingly, I shall only report the chi-square value in my findings and not use it for accepting or rejecting the model.
    - Relative/normed Chi-square (χ^2/df) proposed by Wheaton et al., 1977 for minimizing the impact of sample size. There are multiple recommendations on the acceptable ratio for the relative Chi-square ranging from a ratio of 2.0 (Ullman, 2001, Tabachnick & Fidell, 2007), 3.0 (Kline, 1998) to 5 (Wheaton et al., 1977, Schumacker & Lomax, 2004). I shall only report the relative chi-square value in my findings and not use it for accepting or rejecting the model.
    - Standardized root mean square residual (SRMR) is the square root of the difference between the standardized residuals of the sample and hypothesized covariance matrix. Well-fitted models have an SRMR value less than 0.05 (Byrne, 1998), and values less than 0.08 are considered acceptable (Hu & Bentler, 1999). A large sample size and a high number of parameters will have a low SRMR value. (Hooper et al., 2008).
- **Incremental fit indices** – are comparative indices comparing the Chi-square (χ2) value to a baseline model where the null hypothesis is that all variables are uncorrelated (McDonald and Ho, 2002).

- Non-Normed-fit index (NNFI), also called the Tucker-Lewis Index (TLI), evaluates the model by comparing the Chi-square (χ^2) value of the model to the Chi-square (χ^2) value of the null model, which considers all variables are uncorrelated. A model is considered a good fit if the value $\geq$ 0.9 (Bentler & Bonner, 1980) that in recent publications have been made more stringent to a value $\geq$ 0.95 (Hu & Bentler, 1999). NNFI is susceptible to a small sample size, underestimating fit for samples less than 200 (Mulaik et al., 1989; Bentler, 1990). The index can indicate a model as a poor fit despite other statistics pointing towards a good fit (Bentler, 1990; Kline, 2005; Tabachnick & Fidell, 2007). Since the sample size for my model is below 200, I shall only report the NNFI/TLI value in my findings and not use it for accepting or rejecting the model.
- Bentler, 1990 develop the comparative fit index (CFI). It considers sample size and performs well even when the sample size is small (Tabachnick & Fidell, 2007). It assumes that the latent variables are uncorrelated and compares the model covariance matrix with its null model. A model is considered a good fit if the CFI value $\geq$ 0.9 (Bentler & Bonner, 1980) that, in a recent publication, have been made more stringent to a value $\geq$ 0.95 (Hu & Bentler, 1999) as indicative of a good fit. Since the sample size least affects this index, I shall use it to report my model's goodness of fit.

Many fit indexes are available for assessing the model fit with the data. To avoid biased reporting and use only those indices that include the best fit, I will report all the above indices and use the Two-index (CFI and SRMR) presentation strategy (Hu & Bentler, 1999) to assess my model fit.

Models with a huge degree of freedom (df) are always liable to be mis specified and hence rejected by any "exact" test. SEM involving factor analysis of latent constructs and items of measure dimensions to evaluate models would never fit exactly, but it might fit approximately (Bentler, 2007). In a large multivariate model, there is no single truth to be discovered, and an approximate or "close" fit is right on target.

A CFI value near 0.9 and an SRMR value of 0.08 or lower will be considered to assess the model as a good fit.

4.2c.3 Hypothesis Testing

The model is statistically tested, first at an individual level for each independent variable, then as a model with its interaction variables. Statistical tests are used to assess the credibility of the hypothesis basis the data from a random population sample using the survey instrument. Finally, the model is tested as a complete model to assess whether it still has a statistically significant relationship between the predictor and dependent variables.

5. Results

5.1 Interoperability, Implementation costs, and Vendor lock-in:

The interviews with the SMEs (subject matter experts) highlighted the need for not only interoperability at the device level or syntactic interoperability but a need for having interoperability at various other levels to reduce the cost of implementation for the user, enable integration of solutions and controls at a plant or a business unit level than just at individual equipment or component level. Interoperability requirement drives the industry to standardize to provide efficiency, minimize training needs, and flexibility in choosing the suppliers and reduce the risk of getting lock-in with a vendor over the life cycle. Accordingly, the measure is developed basis the first-order concepts derived from such insights on interoperability, implementation cost for IoT Solutions, and vendor lock-in. The measures are tested for reliability and construct validity of the scale.

a) Construct Robustness

- ***A reliability test*** on the measures for these constructs showed the Cronbach's alpha coefficients of the three components – Interoperability (0.875), Implementation costs (0.885), and Vendor lock-in (0.809) to be higher than the threshold of $\alpha > 0.7$ recommended by Nunnally (1978) for the test of scale reliability. As a measure of internal consistency, Cronbach's alpha α of the variables shows that the items forming the variables are closely related.
- ***Average interitem correlations*** of the items should be roughly the same and cluster narrowly. The average inter-item correlation of the items measuring interoperability ranges from 0.51 to 0.56 (the average inter-item correlation of interoperability is 0.54). It ranges between 0.58 and 0.62 for implementation costs (the average inter-item correlation of implementation cost is 0.61) and between 0.48 and 0.54 for vendor lock-

in (the average inter-item correlation of vendor lock-in is 0.51), indicating that all the items are correlated and are well-fitted.

- For ***convergent validity***, the average variance extracted (AVE) and composite reliability (CR) is examined based on the criterion of Fornell-Larcker (1981). The AVE values for interoperability (0.54), implementation cost (0.608) and vendor lock-in (0.524) have an AVE value above 0.5 indicating adequate convergent validity.
- The composite reliability (CR) values for interoperability (0.87), implementation cost (0.88) and vendor lock-in (0.81) have a CR value above 0.7, indicating adequate internal consistency or convergence.

Table 5

IO, IC & VLI – Construct robustness

Interoperability	Factor Loading	AVE	CR	Average interitem Correlation	Cronbach's Alpha
Device Level	0.6530			0.5668	
Network Level	0.7973			0.5163	
Syntactic	0.7333	0.5419	0.8762	0.5400	0.8752
Operating System Level	0.7402			0.5387	
Platform Level	0.7333			0.5392	
External Partner Level	0.7524			0.5321	
Implementation Cost					
Hardware Cost	0.7744			0.6133	
Software Cost	0.8039			0.5962	
Services Cost	0.8205	0.6084	0.8858	0.5880	0.8853
Data Integration Cost	0.7651			0.6106	
Operating Costs (Subscription/ Maintenance)	0.7331			0.6265	
Vendor Lock-in					
Proprietary Solutions	0.7907	0.5240	0.8137	0.4872	0.8091
Lack of Industry Standards	0.7783			0.4944	

OK for Critical Assets	0.6618	0.5302
OK for Non-Critical Assets	0.6534	0.5460

- The discriminant validity is examined by finding the square root of the AVE and testing its value to be greater than the inter-item correlation (Fornell & Larcker, 1981)

Table 6

IO, IC & VLI – Discriminant validity

Interoperability		q6_1	q6_2	q6_3	q6_4	q6_5	q6_6
Device Level	q6_1	0.7361					
Network Level	q6_2	0.6386	0.7361				
Syntactic	q6_3	0.4492	0.5906	0.7361			
Operating System Level	q6_4	0.3904	0.5599	0.5845	0.7361		
Platform Level	q6_5	0.4794	0.5887	0.4942	0.5454	0.7361	
External Partner Level	q6_6	0.457	0.5417	0.5642	0.6156	0.5834	0.7361

(Square root of the AVE~0.5419=0.7361 is indicated in the cells highlighted in yellow)

Implementation Cost		q7_1	q7_2	q7_3	q7_4	q7_5
Hardware Cost	q7_1	0.7800				
Software Cost	q7_2	0.7015	0.7800			
Services Cost	q7_3	0.6343	0.6224	0.7800		
Data Integration Cost	q7_4	0.5644	0.6099	0.6266	0.7800	
Operating Costs (Subscription/ Maintenance)	q7_5	0.4892	0.5585	0.658	0.6046	0.7800

(Square root of the AVE~0.608=0.78 is indicated in the cells highlighted in yellow)

Vendor Lock-in		q8_1	q8_2	q8_3	q8_4
Proprietary Solutions	q8_1	0.7238			
Lack of Industry Standards	q8_2	0.6384	0.7238		
OK for Critical Assets	q8_3	0.4915	0.5082	0.7238	
OK for Non-Critical Assets	q8_4	0.4952	0.457	0.4965	0.7238

(Square root of the AVE~0.524=0.7238 is indicated in the cells highlighted in yellow)

The testing above demonstrates satisfactory convergent and discriminant (divergent) validity of the items for the Interoperability, Implementation costs, and Vendor lock-in constructs.

b) Model Testing

The relationship between interoperability (IO) and IoT Solutions adoptions (ISA) mediated through implementation costs (IC) and vendor lock-in (VLI) was assessed by evaluating three models–

- Model 1 - Interoperability mediated through Implementation costs
- Model 2 – Interoperability mediated through Vendor Lock-in
- Model 3 – Multi mediation of Interoperability through Implementation costs & Vendor Lock-in

Implementation costs (IC) and Vendor Lock-in (VLI) are hypothesized to have a mediational effect on the relationship between interoperability and ISA adoption. Mediating variables are the causal link in the relationship chain between the IV and DV. In the relationship model between IO and ISA, the two mediating variables of IC and VLI are analyzed separately to test each effect as a causal link and then as a combined model to test the effect of both IC and VLI together as a consolidated model. The direct, indirect, and total effects are analyzed to investigate the mediational role. Using Stata "medsem" macro, a significance test is conducted. Medsem macro allows for post-estimation testing pursuant to estimating the mediational model with the built-in structural equation model (sem) in Stata. It uses Baron & Kenny's (1986) approach modified by Iacobucci et al. (2007) and an alternate approach by Zhao et al., 2010 (Mehmetoglu, 2018). The significance test is conducted to -

i. Test mediation using Baron & Kenny's (1986) approach and Sobel's test (1982) to test whether the effect is significant and whether mediation is partial or complete. The mediation effect is considered significant if the coefficient of IV (IO) on DV (DSA) is reduced by the inclusion of the mediator variable (IC/VLI). Full mediation is when by introducing the mediator variable (IC/VLI), the relationship between the IV (IO) and DV (ISA) is dropped and becomes zero. Partial mediation implies that both the IV (IO) and mediator variables (IC/VLI) have a significant relationship with the DV (ISA).

ii. Test complementary mediation using Zhao, Lynch & Chen's approach and the Monte Carlo test to test the coefficient's significance and direction and whether mediation is partial or complete.

iii. Test the effect size of the indirect effect on the total effect using the ratio of indirect effect to total effect (RIT). The indirect effect measures the extent by which the DV (ISA) changes when the mediating variable (IC/VLI) increases by an extent had the IV(IO) changed by a unit keeping IV(IO) constant (Robins and Greenland, 1992, Pearl J, 2001). It is the product of the coefficients of the direct effect of the IV on the mediator and the mediator on the DV. The total effect in linear regression is the sum of the direct and indirect effects.

iv. Test the effect size of mediation (indirect effect) versus the direct effect of the IV over the DV using a ratio of the indirect effect to the direct effect (RID). The direct effect determines the degree to which the DV (ISA) changes when the IV (IO) increases by a unit, keeping mediator variables intact.

Model 1 - Interoperability mediated through Implementation costs

i. The goodness of fit -

For the model mediated by Implementation costs (IC), the likelihood ratio for the model vs the saturated model, the chi2 $\varkappa 2$ (116) = 265.7, prob>Chi2 = 0.000. The relative chi-square or the normed chi-square (chi-square index divided by the degree of freedom) is 2.29. The comparative fit index (CFI) is 0.924, and Tucker-Lewis Index (TLI), also known as the non-normed fit index (NNFI), is 0.911. The two incremental fit indices should be near zero and preferably more than 0.9 to indicate that the model is acceptable (Byrne, 1994). The standardized root mean square residual (SRMR) for a perfect fit corresponds to 0. A good fit model corresponds to a small value, limited to 0.05 for a close-fitting model and up to 0.1 for an acceptable fit (Pituch & Stevens, 2016). SRMR for the model with IC as a mediator is 0.049. The coefficient of determination (CD) is like an R^2 for the whole model, with a value close to 1 indicating a good model fit. CD for the model is 0.912, indicating an acceptable fit.

Figure 13

IO mediated through IC - Goodness of Fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(116)	265.568	model vs. saturated
p > chi2	0.000	
chi2_bs(136)	2102.340	baseline vs. saturated
p > chi2	0.000	
Baseline comparison		
CFI	0.924	Comparative fit index
TLI	0.911	Tucker-Lewis index
Size of residuals		
SRMR	0.049	Standardized root mean squared residual
CD	0.912	Coefficient of determination

ii. Direct, Indirect, and Total Effect of Mediation

The effect of IC on the relationship between IO and ISA was assessed after validating the model's goodness of fit. The coefficients for the effects are –

Direct effect between IO and ISA = 0.572

Direct effect between IO and IC = -0.635 and between IC and ISA = -0.219

Indirect effect of the mediator IC = -0.635 * -0.219 = 0.139

Total Effect = Direct Effect + Indirect Effect = 0.572+0.139 = 0.711

Figure 14

IO mediated through IC - model with coefficients

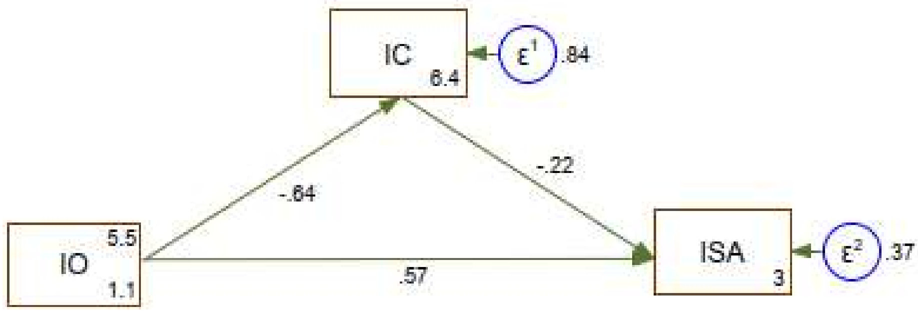


Figure 15

IO mediated through IC - Direct, Indirect and Total Effect

Direct effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	-.6351999	.0633938	-10.02	0.000	-.5839768
ISA					
IC	-.2190775	.0474535	-4.62	0.000	-.2533973
IO	.5724133	.0516158	11.09	0.000	.6086941

Indirect effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	0	(no path)			0
ISA					
IC	0	(no path)			0
IO	.139158	.0331881	4.19	0.000	.1479782

Total effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	-.6351999	.0633938	-10.02	0.000	-.5839768
ISA					
IC	-.2190775	.0474535	-4.62	0.000	-.2533973
IO	.7115713	.0441419	16.12	0.000	.7566722

According to Kenny (2016), an indirect effect size of 0.01 would be considered a small effect, up to 0.09 as a medium effect, and a large effect at 0.25. These values are squared of the effect size recommended by Shrout & Bolger (2002) and Cohen (1988) standards of 0.1 for small, 0.3 for medium, and 0.5 for large effect as the coefficients are multiplied for the indirect effect of mediating variable. The indirect effect of IC on the relationship between IO and ISA is 0.139, indicating a mediation effect.

iii. Significance Test for Mediation

Figure 16

IO mediated through IC - Significance test of indirect effect

Significance testing of indirect effect (unstandardised)

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	0.139	0.139	0.142
Std. Err.	0.033	0.033	0.035
z-value	4.193	4.193	4.008
p-value	0.000	0.000	0.000
Conf. Interval	0.074 , 0.204	0.074 , 0.204	0.076 , 0.215

```
*You typed in mcreps < #of obs, your mcreps is however set to #of obs!

Baron and Kenny approach to testing mediation
STEP 1 - IC:IO (X -> M) with B=-0.635 and p=0.000
STEP 2 - ISA:IC (M -> Y) with B=-0.219 and p=0.000
STEP 3 - ISA:IO (X -> Y) with B=0.572 and p=0.000
         As STEP 1, STEP 2 and STEP 3 as well as the Sobel's test above
         are significant the mediation is partial!

Zhao, Lynch & Chen's approach to testing mediation
STEP 1 - ISA:IO (X -> Y) with B=0.572 and p=0.000
         As the Monte Carlo test above is significant, STEP 1 is
         significant and their coefficients point in same direction,
         you have complementary mediation (partial mediation)!

RIT  =   (Indirect effect / Total effect)
         (0.139 / 0.712) = 0.196
         Meaning that about 20 % of the effect of IO
         on ISA is mediated by IC!

RID  =   (Indirect effect / Direct effect)
         (0.139 / 0.572) = 0.243
         That is, the mediated effect is about 0.2 times as
         large as the direct effect of IO on ISA!
```

The mediation is partial and significant in both Sobels and ZLC (Zhao, Lynch, and Chen's) test. Further, the indirect effect of IC accounts for 19.6% of the total effect of IO on ISA, and the direct effect is 4.11 times (1/0.243 –> RID) greater than the indirect effect.

iv. Model Specification

Per Baron and Kenny's (1986) steps for mediation analysis,

Step 1 – Regress the DV (ISA) on the IV (IO) to test that the IV (IO) is a significant predictor of the DV (ISA).

$$ISA = (1.626)\ \beta_{10} + (0.7115)\ \beta_{11}\ (IO)\ (\beta_{11} \text{ is significant})$$

Step 2 – Regress the mediator (IC) on the IV (IO) to test that the IV (IO) is a significant predictor of the mediator (IC).

$$IC = (6.377)\ \beta_{20} + (-0.635)\ \beta_{21}\ (IO) \quad (\beta_{21} \text{ is significant})$$

Step 3 – Regress the DV (ISA) on both the IV (IO) and mediator (IC) to test that the mediator (IC) is a significant predictor of the DV (ISA) and that the strength of the coefficient for the IV(IO) is reduced.

$$ISA = (3.023)\ \beta_{30} + (0.572)\ \beta_{31}\ (IO) + (-0.219)\ \beta_{32}\ (IC)$$

(β_{32} is significant & β_{31}(0.572) is smaller in absolute value than the original effect β_{11} (0.7115)).

Figure 17

IO mediated through IC – Regression coefficients

	(1) ISA	(2) IC	(3) ISA
IO	0.712***	-0.635***	0.572***
	(16.04)	(-9.97)	(11.00)
IC			-0.219***
			(-4.58)
_cons	1.626***	6.377***	3.023***
	(6.51)	(17.77)	(7.82)
N	194	194	194
df_m	1	1	2
df_r	192	192	191
F	257.2	99.36	152.5
r2	0.573	0.341	0.615
rmse	0.641	0.920	0.610

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The hypothesis test results show that –

- there is a significant total effect between interoperability and IoT Solution adoption (β $=0.7115$, $p <.001$)
- path from Interoperability to Implementation costs ($\beta = -0.635$, $p <.001$) is significant
- path from Implementation costs on IoT Solution adoption ($\beta = -0.219$, $p <.001$) is significant
- Finally, when Implementation costs entered the relationship between interoperability and IoT Solution adoption, the direct effect ($\beta =0.572$, $p <.001$) was significant.
- Sobel test for the indirect effect is $z = 4.193$, $p <.001$; therefore, it is concluded that a partial mediation occurred between interoperability on IoT Solution adoption via Implementation costs.

Following the assessment and testing of the model for –

- The goodness of fit
- The direct, indirect, and total effect of the mediation of implementation cost on the relationship between interoperability and IoT Solution adoption,
- Significance test for mediation

I find support for the mediational hypothesis, i.e., interoperability reduces the implementation cost (negative relation), and reduction in implementation cost increases the adoption of IoT solutions (negative relation).

Model 2 - Interoperability mediated through Vendor Lock-in

i. Goodness of fit

For the model mediated by Vendor Lock-in (VLI), the likelihood ratio for the model vs. the saturated model, the chi2 $\varkappa 2$ (101) = 247.9, prob>Chi2 = 0.000. The relative chi-square or the normed chi-square (chi-square index divided by the degree of freedom) is 2.45. The comparative fit index (CFI) is 0.915, and Tucker-Lewis Index (TLI), also known as the non-normed fit index (NNFI), is 0.899. The two incremental fit indices should be near zero and preferably more than 0.9 to indicate that the model is acceptable (Byrne, 1994). The standardized root mean square residual (SRMR) for a perfect fit corresponds to 0. A good fit model corresponds to a small value, limited to 0.05 for a close-fitting model and up to 0.1 for an acceptable fit (Pituch & Stevens, 2016). SRMR for the model with IC as a mediator is 0.055. The coefficient of determination (CD) is like an R^2 for the whole model, with a value close to 1 indicating a good model fit. CD for the model is 0.912, indicating an acceptable fit.

Figure 18

IO mediated through VLI - Goodness of Fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(101)	247.182	model vs. saturated
p > chi2	0.000	
chi2_bs(120)	1843.657	baseline vs. saturated
p > chi2	0.000	
Baseline comparison		
CFI	0.915	Comparative fit index
TLI	0.899	Tucker-Lewis index
Size of residuals		
SRMR	0.055	Standardized root mean squared residual
CD	0.912	Coefficient of determination

ii. Direct, Indirect, and Total Effect of Mediation

The effect of VLI on the relationship between IO and ISA was assessed after validating the model's goodness of fit. The coefficients for the effects are –

Direct effect between IO and ISA = 0.552

Direct effect between IO and VLI = -0.612 and between VLI and ISA = -0.261

Indirect effect of the mediator VLI = -0.612 * -0.261 = 0.1597

Total Effect = Direct Effect + Indirect Effect = 0.552+0.1597 = 0.7117

Figure 19

IO mediated through VLI – Model with coefficient

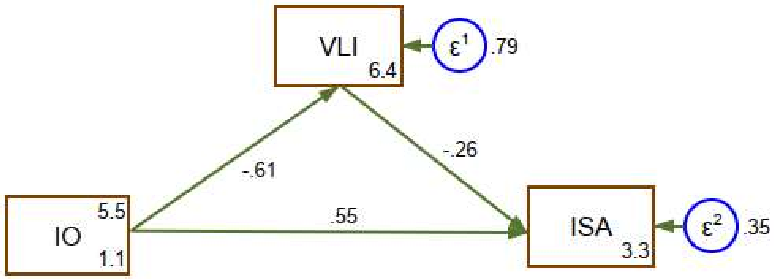


Figure 20

IO mediated through VLI – Direct, Indirect and Total Effect

Direct effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
VLI					
IO	-.6121901	.0615097	-9.95	0.000	-.5813887
ISA					
VLI	-.2606733	.0480044	-5.43	0.000	-.2918808
IO	.5519897	.0505476	10.92	0.000	.586976

Indirect effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
VLI					
IO	0	(no path)			0
ISA					
VLI	0	(no path)			0
IO	.1595816	.0334773	4.77	0.000	.1696962

Total effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
VLI					
IO	-.6121901	.0615097	-9.95	0.000	-.5813887
ISA					
VLI	-.2606733	.0480044	-5.43	0.000	-.2918808
IO	.7115713	.0441419	16.12	0.000	.7566722

According to Kenny, 2016 an indirect effect size of 0.01 would be considered a small effect, up to 0.09 as a medium effect, and a large effect at 0.25. These values are squared of the effect size recommended by Shrout & Bolger (2002) and Cohen (1988) standards of 0.1 for small, 0.3 for medium, and 0.5 for large effect as the coefficients are multiplied for the indirect effect of mediating variable. The indirect effect of VLI on the relationship between IO and ISA is 0.159, indicating a mediation effect.

iii. Significance Test for Mediation

Figure 21

IO mediated through VLI – Significance test of indirect effect

Significance testing of indirect effect (unstandardised)

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	0.160	0.160	0.162
Std. Err.	0.033	0.033	0.036
z-value	4.767	4.767	4.561
p-value	0.000	0.000	0.000
Conf. Interval	0.094 , 0.225	0.094 , 0.225	0.096 , 0.235

```
*You typed in mcreps < #of obs, your mcreps is however set to #of obs!

Baron and Kenny approach to testing mediation
STEP 1 - VLI:IO (X -> M) with B=-0.612 and p=0.000
STEP 2 - ISA:VLI (M -> Y) with B=-0.261 and p=0.000
STEP 3 - ISA:IO (X -> Y) with B=0.552 and p=0.000
         As STEP 1, STEP 2 and STEP 3 as well as the Sobel's test above
         are significant the mediation is partial!

Zhao, Lynch & Chen's approach to testing mediation
STEP 1 - ISA:IO (X -> Y) with B=0.552 and p=0.000
         As the Monte Carlo test above is significant, STEP 1 is
         significant and their coefficients point in same direction,
         you have complementary mediation (partial mediation)!

RIT  =   (Indirect effect / Total effect)
         (0.160 / 0.712) = 0.224
         Meaning that about 22 % of the effect of IO
         on ISA is mediated by VLI!

RID  =   (Indirect effect / Direct effect)
         (0.160 / 0.552) = 0.289
         That is, the mediated effect is about 0.3 times as
         large as the direct effect of IO on ISA!
```

The mediation is partial and significant in both Sobels and ZLC (Zhao, Lynch, and Chen's) test. It supports the mediational hypothesis, i.e., interoperability reduces the implementation cost (negative relation), and reduction in implementation cost increases the adoption of IoT solutions (negative relation). Further, 22.4% of the total effect of IO on ISA is accounted for by the indirect effect of VLI, and the direct effect is 3.33 times (1/0.3 –> RID) greater than the indirect effect.

iv. Model Specification

Per Baron and Kenny's (1986) steps for mediation analysis,

Step 1 – Regress the DV (ISA) on the IV (IO) to test that the IV (IO) is a significant predictor of the DV (ISA).

$$ISA = (1.626)\ \beta_{10} + (0.7115)\ \beta_{11}\ (IO)\ (\beta_{11} \text{ is significant})$$

Step 2 – Regress the mediator (VLI) on the IV (IO) to test that the IV (IO) is a significant predictor of the mediator (VLI).

$$VLI = (6.377)\ \beta 20 + (-0.612)\ \beta_{21}\ (IO) \qquad (\beta_{21} \text{ is significant})$$

Step 3 – Regress the DV (ISA) on both the IV (IO) and mediator (VLI) to test that the mediator (VLI) is a significant predictor of the DV (ISA) and that the strength of the coefficient for the IV(IO) is reduced.

$$ISA = (3.287)\ \beta_{30} + (0.552)\ \beta_{31}\ (IO) + (-0.261)\ \beta_{32}\ (VLI)$$

(β_{32} is significant & β_{31} is smaller in absolute value than the original effect β_{11})

Figure 22

IO mediated through VLI – Regression Coefficients

	(1) ISA	(2) VLI	(3) ISA
IO	0.712***	-0.612***	0.552***
	(16.04)	(-9.90)	(10.84)
VLI			-0.261***
			(-5.39)
_cons	1.626***	6.374***	3.287***
	(6.51)	(18.30)	(8.50)
N	194	194	194
df_m	1	1	2
df_r	192	192	191
F	257.2	98.04	161.9
r2	0.573	0.338	0.629
rmse	0.641	0.893	0.599

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The hypothesis test results show that –

- there is a significant total effect between interoperability and IoT Solution adoption ($\beta =0.7115$, p <.001)
- path from Interoperability to Vendor lock-in ($\beta = -0.612$, p <.001) is significant
- path from Vendor lock-in on IoT Solution adoption ($\beta = -0.261$, p <.001) is significant
- Finally, when Vendor lock-in entered the relationship between interoperability and IoT Solution adoption, the direct effect ($\beta =0.552$, p <.001) was significant.
- Sobel test for the indirect effect is z = 4.767, p <.001; therefore, it is concluded that a partial mediation occurred between interoperability on IoT Solution adoption via Vendor lock-in.

Following the assessment and testing of the model for –

- The goodness of fit
- The direct, indirect, and total effect of the mediation of implementation cost on the relationship between interoperability and IoT Solution adoption,
- Significance test for mediation

I find support for the mediational hypothesis, i.e., interoperability reduces the vendor lock-in (negative relation), and reduction in vendor lock-in increases the adoption of IoT solutions (negative relation).

Model 3 - Multi mediation of Interoperability through Implementation costs & Vendor Lock-in

i. The goodness of fit

For the multi-mediated model, mediated by Implementation costs (IC) and Vendor Lock-in, the likelihood ratio for the model vs. the saturated model, the chi2 $\varkappa 2$ (184) = 431.92, prob>Chi2 = 0.000. The relative chi-square or the normed chi-square (chi-square index divided by the degree of freedom) is 2.34. The comparative fit index (CFI) is 0.897, and Tucker-Lewis Index (TLI), also known as the non-normed fit index (NNFI), is 0.883. The two incremental fit indices should be near zero and preferably more than 0.9 to indicate that the model is acceptable (Byrne, 1994). The standardized root mean square residual (SRMR) for a perfect fit corresponds to 0. A good fit model corresponds to a small value, limited to 0.05 for a close-fitting model and up to 0.1 for an acceptable fit (Pituch & Stevens, 2016). SRMR for the model with IC and VLI as a mediator is 0.060. The coefficient of determination (CD) is like an R^2 for the whole model, with a value close to 1 indicating a good model fit. CD for the model is 0.918, indicating an acceptable fit.

Figure 23

Multi mediation of IO through IC & VLI - Goodness of Fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(184)	431.915	model vs. saturated
p > chi2	0.000	
chi2_bs(210)	2619.129	baseline vs. saturated
p > chi2	0.000	
Baseline comparison		
CFI	0.897	Comparative fit index
TLI	0.883	Tucker-Lewis index
Size of residuals		
SRMR	0.060	Standardized root mean squared residual
CD	0.918	Coefficient of determination

ii. Direct, Indirect, and Total Effect of Mediation

The effect of IC on the relationship between IO and ISA was assessed after validating the model's goodness of fit. The coefficients for the effects are –

Direct effect between IO and ISA = 0.476

Direct effect between IO and IC = -0.635 and between IC and ISA = -0.162

Direct effect between IO and VLI = -0.612 and between VLI and ISA = -0.215

Total Effect = 0.712

Figure 24

Multi mediation of IO through IC & VLI - model with coefficients

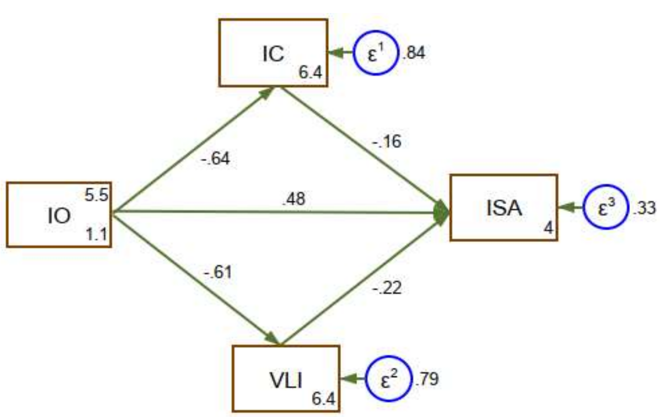


Figure 25

Multi mediation of IO through IC & VLI - Direct, Indirect and Total Effect

Direct effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	-.6351999	.0633938	-10.02	0.000	-.5839768
VLI					
IO	-.6121901	.0615097	-9.95	0.000	-.5813887
ISA					
IC	-.1624886	.0469592	-3.46	0.001	-.1894857
VLI	-.215311	.0483977	-4.45	0.000	-.2430662
IO	.4765474	.0536834	8.88	0.000	.5109105

Indirect effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	0	(no path)			0
VLI					
IO	0	(no path)			0
ISA					
IC	0	(no path)			0
VLI	0	(no path)			0
IO	.235024	.0396271	5.93	0.000	.2519712

Total effects

	Coefficient	OIM std. err.	z	P>|z|	Std. coef.
Structural					
IC					
IO	-.6351999	.0633938	-10.02	0.000	-.5839768
VLI					
IO	-.6121901	.0615097	-9.95	0.000	-.5813887
ISA					
IC	-.1624886	.0469592	-3.46	0.001	-.1894857
VLI	-.215311	.0483977	-4.45	0.000	-.2430662
IO	.7115713	.0432967	16.43	0.000	.7628817

According to Kenny, 2016 an indirect effect size of 0.01 would be considered a small effect, up to 0.09 as a medium effect, and a large effect at 0.25. These values are squared of the effect size recommended by Shrout & Bolger (2002) and Cohen (1988) standards of 0.1 for small, 0.3 for medium, and 0.5 for large effect as the coefficients are multiplied for the indirect effect of mediating variable. The indirect effect of IC and VLI on the relationship between IO and ISA is 0.235, indicating a mediation effect.

iii. Significance Test for Mediation

Medsem package was run in Stata to test the multiple mediations of IC and VLI on the relationship between IO and ISA.

Figure 26

Multi mediation of IO through IC - Significance test of indirect effect

Significance testing of indirect effect (unstandardised)

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	0.103	0.103	0.106
Std. Err.	0.032	0.032	0.034
z-value	3.271	3.271	3.136
p-value	0.001	0.001	0.002
Conf. Interval	0.041 , 0.165	0.041 , 0.165	0.043 , 0.178

```
*You typed in mcreps < #of obs, your mcreps is however set to #of obs!

Baron and Kenny approach to testing mediation
STEP 1 - IC:IO (X -> M) with B=-0.635 and p=0.000
STEP 2 - ISA:IC (M -> Y) with B=-0.162 and p=0.001
STEP 3 - ISA:IO (X -> Y) with B=0.477 and p=0.000
         As STEP 1, STEP 2 and STEP 3 as well as the Sobel's test above
         are significant the mediation is partial!

Zhao, Lynch & Chen's approach to testing mediation
STEP 1 - ISA:IO (X -> Y) with B=0.477 and p=0.000
         As the Monte Carlo test above is significant, STEP 1 is
         significant and their coefficients point in same direction,
         you have complementary mediation (partial mediation)!

RIT  =   (Indirect effect / Total effect)
         (0.103 / 0.580) = 0.178
         Meaning that about 18 % of the effect of IO
         on ISA is mediated by IC!

RID  =   (Indirect effect / Direct effect)
         (0.103 / 0.477) = 0.217
         That is, the mediated effect is about 0.2 times as
         large as the direct effect of IO on ISA!
```

The mediation is partial and significant in both Sobels and ZLC (Zhao, Lynch, and Chen's) test. Further, the indirect effect of IC accounts for 17.8% of the total effect, and the direct effect is 4.6 times (1/0.217 –> RID) greater than the indirect effect.

Figure 27

Multi mediation of IO through VLI - Significance test of indirect effect

Significance testing of indirect effect (unstandardised)

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	0.132	0.132	0.135
Std. Err.	0.032	0.032	0.035
z-value	4.062	4.062	3.883
p-value	0.000	0.000	0.000
Conf. Interval	0.068 , 0.195	0.068 , 0.195	0.070 , 0.206

*You typed in mcreps < #of obs, your mcreps is however set to #of obs!

```
Baron and Kenny approach to testing mediation
STEP 1 - VLI:IO (X -> M) with B=-0.612 and p=0.000
STEP 2 - ISA:VLI (M -> Y) with B=-0.215 and p=0.000
STEP 3 - ISA:IO (X -> Y) with B=0.477 and p=0.000
         As STEP 1, STEP 2 and STEP 3 as well as the Sobel's test above
         are significant the mediation is partial!

Zhao, Lynch & Chen's approach to testing mediation
STEP 1 - ISA:IO (X -> Y) with B=0.477 and p=0.000
         As the Monte Carlo test above is significant, STEP 1 is
         significant and their coefficients point in same direction,
         you have complementary mediation (partial mediation)!

RIT  =   (Indirect effect / Total effect)
         (0.132 / 0.608) = 0.217
         Meaning that about 22 % of the effect of IO
         on ISA is mediated by VLI!

RID  =   (Indirect effect / Direct effect)
         (0.132 / 0.477) = 0.277
         That is, the mediated effect is about 0.3 times as
         large as the direct effect of IO on ISA!
```

The mediation is partial and significant in both Sobels and ZLC (Zhao, Lynch, and Chen's) test. Further, the indirect effect of IC accounts for 21.7% of the total effect, and the direct effect is 3.3 times (1/0.3 –> RID) greater than the indirect effect.

Figure 28

Multi mediation of IO through IC - Regression coefficients

	(1) IC
IC	
IO	-0.635***
	(-10.02)
_cons	6.377***
	(17.86)
VLI	
IO	-0.612***
	(-9.95)
_cons	6.374***
	(18.40)
ISA	
IC	-0.162***
	(-3.46)
VLI	-0.215***
	(-4.45)
IO	0.477***
	(8.88)
_cons	4.035***
	(9.37)
N	194
r2	0.341
rmse	0.916

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The hypothesis test results show that –

- there is a significant total effect between interoperability and IoT Solution adoption (β $=0.7115$, p <.001)
- path from Interoperability to Implementation costs (β = -0.635, p <.001) and from Interoperability to Vendor lock-in (β = -0.612, p <.001) is significant
- path from Implementation costs on IoT Solution adoption (β = -0.162, p <.001) and from Vendor lock-in on IoT Solution adoption (β = -0.215, p <.001) is significant

- Finally, when Implementation costs and Vendor lock-in entered the relationship between interoperability and IoT Solution adoption, the direct effect (*β =0.477*, p <.001) was significant.
- Sobel test for the indirect effect of implementation cost is z = 3.271, p <.001, and for vendor lock-in is z = 4.062, p <.001; therefore, it is concluded that a partial mediation occurred between interoperability on IoT Solution adoption via implementation cost and Vendor lock-in.

Following the assessment and testing of the model for –

- The goodness of fit
- The direct, indirect, and total effect of the mediation of implementation cost on the relationship between interoperability and IoT Solution adoption,
- Significance test for mediation

I find support for the mediational hypothesis, i.e., interoperability reduces the implementation cost and vendor lock-in (negative relation), and reduction in implementation cost and vendor lock-in increases the adoption of IoT solutions (negative relation).

5.2 Asset Criticality and Responsiveness

A manufacturing plant, a process plant, or any operation in the industry needs multiple machines/equipment to deliver the final product. These equipment/machineries are termed assets in the company's balance sheet. All the assets in a plant are not equally important or mission-critical for the success of the operations. The interviews with the SMEs (subject matter experts) revealed a split opinion on implementing IoT solutions between critical and non-critical assets. Almost half of the interviewed SMEs wanted the critical equipment as a priority to implement IoT Solutions to help with the operational reliability of the equipment. The remaining SMEs wanted non-critical assets to be prioritized for implementation as they still wanted to gain the confidence that the IoT solutions provided would deliver the promised benefits and reduce risks. Besides, different functions within a company have their views on what is considered critical. The interviews also highlighted that the responsiveness of service providers to maintain the equipment to its optimum operations affects the asset's categorization as critical and the decision to implement the IoT Solution for that asset. A variable is considered a moderator if the size, sign, or strength of the relationship between the IV and DV depends on or can be predicted by it (Hayes, A.F., 2014). It is thus hypothesized that responsiveness has a mediating role in the relationship between asset criticality and IoT Solution Adoption.

Accordingly, the measure is developed basis the first-order concepts derived from such insights on asset criticality and responsiveness. The measures are tested for reliability and construct validity of the scale.

a) Construct Robustness

- A **reliability test** on the measures for these constructs in the affective domain showed Cronbach's alpha coefficients of the three components – Asset Criticality (0.906) and responsiveness (0.851) to be higher than the threshold recommended by Nunnally (1978) for the test of scale reliability. As a measure of internal consistency, Cronbach's alpha value of the variables shows that the items forming the variables are closely related.
- **Average interitem correlations** of the items should be roughly the same and cluster narrowly. The average inter-item correlation of the Items measuring asset criticality ranges from 0.52 to 0.57 (the average inter-item correlation of asset criticality is 0.54). It ranges between 0.55 and 0.63 for responsiveness (the average inter-item correlation of implementation cost is 0.59), indicating that all the items are correlated and fitted.

- For **convergent validity**, the average variance extracted (AVE) and composite reliability (CR) is examined based on the criterion of Fornell-Larcker (1981). AVE measures the ratio of variance captured by a construct versus the level due to measurement error. Standardized loading estimates of the times 0.5 or higher show convergent validity. The AVE values for asset criticality (0.57) and responsiveness (0.59) have an AVE value above 0.5, indicating adequate convergent validity.
- The **composite reliability** (CR) is expected to have a value of 0.7 or higher. The CR values for asset criticality (0.91) and responsiveness (0.85) have a CR value above 0.7, indicating adequate internal consistency or convergence.

Table 7

AC, R - Construct Robustness

Critical Assets	Factor Loading	AVE	CR	Average interitem Correlation	Cronbach's Alpha
Affect Production Capacity	0.5772			0.5743	
Affect Safety	0.6181			0.5625	
Unspared Unit / No Redundancy	0.7854			0.5353	
Supplier Monopoly	0.7596			0.5401	
Insufficient In-house Maintenance	0.7946	0.5665	0.9094	0.5383	0.9058
Supplier inability for fast service response	0.8674			0.5212	
First Cost High / Expensive Equipment	0.7977			0.5350	
Bad Actor / Frequent Failing Equipment	0.7017			0.5622	
Responsiveness					
Procedures & Processes	0.7788			0.5936	
Life Cycle Reliability	0.8416	0.5904	0.8515	0.5528	0.8505
Turnaround time	0.7616			0.5749	

Competent Service Personnel	0.6833	0.6274

The **discriminant validity** is examined by finding the square root of the AVE and testing its value to be greater than the inter-item correlation (Fornell and Larcker, 1981)

Table *8*

AC,R - Discriminant validity

Asset Criticality		q9_1	q9_2	q9_3	q9_4	q9_5	q9_6	q9_7	q9_8
Affect Production Capacity	q9_1	0.7526							
Affect Safety	q9_2	0.7036	0.7526						
Unspared Unit / No Redundancy	q9_3	0.4166	0.5564	0.7526					
Supplier Monopoly	q9_4	0.5156	0.4774	0.5916	0.7526				
Insufficient In-house Maintenance	q9_5	0.4085	0.4631	0.6392	0.5892	0.7526			
Supplier inability for fast service response	q9_6	0.4757	0.501	0.6696	0.6375	0.7198	0.7526		
First Cost High / Expensive Equipment	q9_7	0.4576	0.408	0.6034	0.6596	0.6256	0.6867	0.7526	
Bad Actor / Frequent Failing Equipment	q9_8	0.254	0.369	0.5724	0.4783	0.5416	0.6556	0.6144	0.7526

(Square root of the AVE~0.5665=0.7526 is indicated in the cells highlighted in yellow)

Responsiveness		q10_1	q10_2	q10_3	q10_4
Procedures & Processes	q10_1	0.7684			
Life Cycle Reliability	q10_2	0.6907	0.7684		
Turnaround time	q10_3	0.5801	0.6115	0.7684	
Competent Service Personnel	q10_4	0.4715	0.5625	0.6069	0.7684

(Square root of the AVE~0.5904=0.7684 is indicated in the cells highlighted in yellow)

The testing above demonstrates satisfactory convergent and divergent validity of the items for asset criticality and responsiveness constructs.

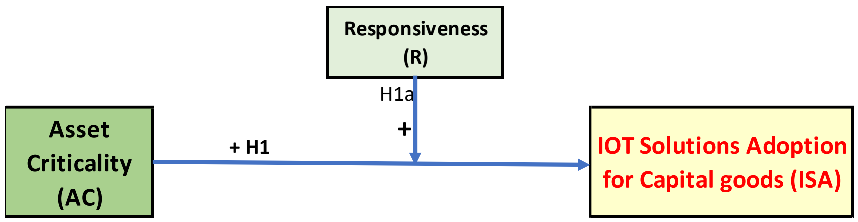
b) Model Testing

Responsiveness (R) is hypothesized to moderate the relationship between asset criticality (AC) and IoT Solutions Adoption (ISA). The relationship is investigated analytically and tested for responsiveness and asset criticality interacting in their influence on IoT Solutions Adoption. The conceptual model with the IV and a moderator is converted into a statistical model with three antecedent variables.

Conceptual Model

Figure 29

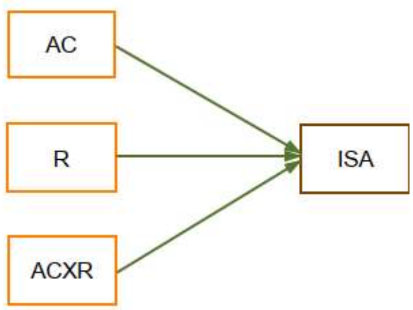
Conceptual Moderating Model – interaction of R on AC and ISA



Statistical Model

Figure 30

Statistical Moderating Model – interaction of R on AC and ISA



i. The goodness of fit

For the model moderated by responsiveness (R), the likelihood ratio for the model vs. the saturated model, the chi2 ϰ2 (147) = 449.59, prob>Chi2 = 0.000. The relative chi-square or the normed chi-square (chi-square index divided by the degree of freedom) is 3.06. The comparative fit index (CFI) is 0.899, and Tucker-Lewis Index (TLI), also known as the non-normed fit index (NNFI), is 0.882. The two incremental fit indices should be near zero and preferably more than 0.9 to indicate that the model is acceptable (Byrne, 1994). The standardized root mean square residual (SRMR) for a perfect fit corresponds to 0. A good fit model corresponds to a small value, limited to 0.05 for a close-fitting model and up to 0.1 for an acceptable fit (Pituch & Stevens, 2016). SRMR for the model with IC as a mediator is 0.080. The coefficient of determination (CD) is like an R^2 for the whole model, with a value close to

1 indicating a good model fit. CD for the model is 0.982, indicating an acceptable fit. The CFI/TLI values are near the threshold limits, whereas the residuals indicate a good fit; hence I continue to test the model for statistical significance.

Figure 31

Interaction of R on AC and ISA - Goodness of Fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(147)	449.588	model vs. saturated
p > chi2	0.000	
chi2_bs(171)	3155.219	baseline vs. saturated
p > chi2	0.000	
Baseline comparison		
CFI	0.899	Comparative fit index
TLI	0.882	Tucker-Lewis index
Size of residuals		
SRMR	0.080	Standardized root mean squared residual
CD	0.982	Coefficient of determination

ii. Significance Test for Moderation

The regression model for the relationship between asset criticality (AC), responsiveness (R), and interacting term of ACXR with IoT solutions adoption (ISA), respectively, indicates the relationships to be positive and statistically significant.

Figure 32

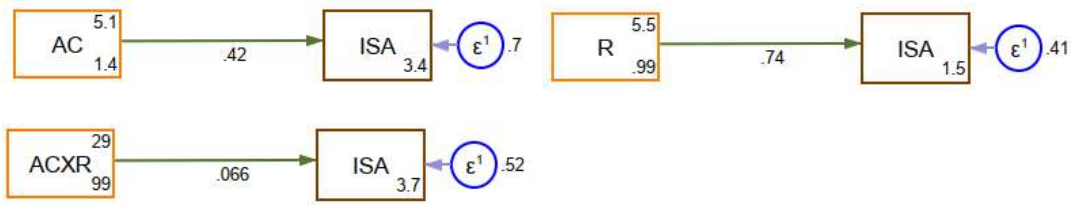
Interaction of R on AC and ISA – Regression coefficients

	(1) ISA	(2) ISA	(3) ISA
AC	0.423***		
	(8.26)		
R		0.740***	
		(15.92)	
ACXR			0.0658***
			(12.52)
_cons	3.408***	1.484***	3.675***
	(12.71)	(5.70)	(23.02)
N	194	194	194
df_m	1	1	1
df_r	192	192	192
F	68.17	253.3	156.9
r2	0.262	0.569	0.450
rmse	0.842	0.644	0.727

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 33

Interaction of R on AC and ISA – model with coefficients



After checking the variables at an individual level, the complete model is tested. Hierarchical multiple regression using nestreg command in stata is used to generate two regression models – model 1 excluding the interaction term and model 2 including it. The change in R-square from model 1 to model 2 reflects the unique contribution of the interaction between AC and R in explaining the variation in ISA.

$$\textit{Model 1}: \hat{y} = \beta 0 + \beta 1\,(AC) + \beta 2\,(R)$$
$$\textit{Model 2}: \hat{y} = \beta 0 + \beta 1\,(AC) + \beta 2\,(R) + \beta 3\,(ACXR)$$

Figure 34

Interaction of R on AC and ISA – regression model without interaction effect

Block 1: **AC_mc R_mc**

Source	SS	df	MS
Model	108.199039	2	54.0995197
Residual	76.3072647	191	.399514475
Total	184.506304	193	.955991213

Number of obs	=	194
F(2, 191)	=	135.41
Prob > F	=	0.0000
R-squared	=	0.5864
Adj R-squared	=	0.5821
Root MSE	=	.63207

ISA	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
AC_mc	.1292339	.0453515	2.85	0.005	.0397798	.218688
R_mc	.6587162	.0538156	12.24	0.000	.5525669	.7648654
_cons	5.565292	.0453801	122.64	0.000	5.475782	5.654803

Model 1 (Block 1) is the regression model without the interacting effect of the moderating variable R. The regression coefficients for each predictor variable (IV) AC and R reflect the partial effect (Darlington & Hayes, 2017) or unconditional effect (Hayes, 2018) between the predictor and ISA. Each coefficient represents the predicted change in ISA per unit increment

on the IV (e.g., AC), holding the remaining IVs (e.g., R) constant. It represents a simple slope. The regression slope for AC (b=0.129) indicates that differing one unit of AC is expected to differ ISA by 0.129 units, holding R constant positively. Similarly, the regression slope for R (b=0.659) indicates that differing one unit of R is expected to differ ISA by 0.659 units, holding AC constant positively.

Model 1 : $\hat{y} = (5.565)\ \beta 0 + (0.129)\ \beta 1\ (AC) + (0.658)\ \beta 2\ (R)$

Figure 35

Interaction of R on AC and ISA – regression model with interaction effect

Source	SS	df	MS			
				Number of obs	=	194
				F(3, 190)	=	95.81
Model	111.081063	3	37.027021	Prob > F	=	0.0000
Residual	73.4252411	190	.386448638	R-squared	=	0.6020
				Adj R-squared	=	0.5958
Total	184.506304	193	.955991213	Root MSE	=	.62165

ISA	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
AC_mc	.1413394	.0448235	3.15	0.002	.0529238	.2297549
R_mc	.6105919	.0557848	10.95	0.000	.5005547	.720629
interact	-.090755	.0332329	-2.73	0.007	-.1563078	-.0252023
_cons	5.621644	.0491713	114.33	0.000	5.524653	5.718636

Model 2 *: $\hat{y} = (5.621)\ \beta 0 + (0.141)\ \beta 1\ (AC) + (0.611)\ \beta 2\ (R) + (-0.091)\ \beta 3\ (ACXR)$*

Model 2 (Block 2) is the regression model with the moderating variable R interacting effect. The regression slope for AC (0.141) represents the effect of AC on ISA adoption, with R being 0. Similarly, the regression slope for R (0.611) represents R's effect on ISA adoption, with AC being 0. The regression slope for the interaction term, ACXR (-0.091), represents the predicted change in the conditional effect/slope for AC for each unit increase of R (Hayes, 2018). In other words, when the value of AC increases by one unit, the slope of the relationship between R and ISA decreases by the interaction term (negative interaction term), i.e., when AC is one, the slope of the relationship between R and ISA is 0.61-0.09 = 0.52. The interaction term ACXR test is statistically significant ($p < 0.05$).

The differences between the two models are summarised in the table below-

Figure 36

Interaction of R on AC and ISA – Difference between with and without interaction

Block	F	Block df	Residual df	Pr > F	R2	Change in R2
1	135.41	2	191	0.0000	0.5864	
2	7.46	1	190	0.0069	0.6020	0.0156

R-square value has a positive increment of 0.0156 (1.56%) in model 2 with interaction/ conditional effect over the model 1 (partial / unconditional effect). The F-test is significant ($p<0.05$), indicating that the interaction term contributes significantly to the model.

Given the finding of a significant interaction effect, a graph is plotted for the conditional relationship between asset criticality and IoT Solutions adoption at a different level of responsiveness at the mean-1sd (standard deviation), at the mean, and at the mean+1sd. Stata computed the simple slopes for AC on R, and the values of the dy/dx tabulated below

Figure 37

Interaction of R on AC and ISA – linear prediction - slope of AC on R

```
Expression: Linear prediction, predict()
dy/dx wrt:  AC_mc
1._at: R_mc = -.9966358
2._at: R_mc =         0
3._at: R_mc =  .9966358
```

	dy/dx	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
AC_mc						
_at						
1	.2317891	.0583077	3.98	0.000	.1167755	.3468026
2	.1413394	.0448235	3.15	0.002	.0529238	.2297549
3	.0508897	.0530331	0.96	0.338	-.0537196	.1554989

The results indicate that the simple slope for AC at 1sd below the mean on R is 0.232, which is statistically significant ($p<0.05$). The simple slope at the mean on R is 0.141 (also significant at $p<0.05$). At 1sd above the mean, the simple slope is 0.051 and is non-significant.

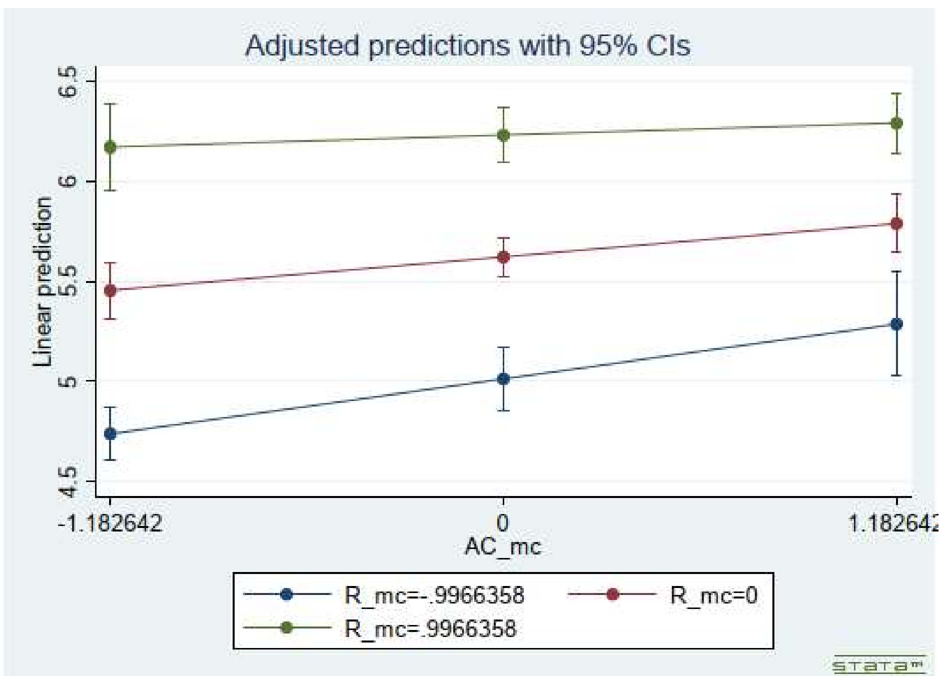
Overall, the conditional effect of AC on ISA becomes less positive as we move from lower levels of responsiveness to higher levels of responsiveness.

0.232 > 0.141 > 0.05

1 sd below   mean   1 sd above

Figure 38

Interaction of R on AC and ISA - graphical plat of slope of AC on R



```
Expression: Linear prediction, predict()
1._at: AC_mc = -1.182642
       R_mc  = -.9966358
2._at: AC_mc = -1.182642
       R_mc  =         0
3._at: AC_mc = -1.182642
       R_mc  =  .9966358
4._at: AC_mc =         0
       R_mc  = -.9966358
5._at: AC_mc =         0
       R_mc  =         0
6._at: AC_mc =         0
       R_mc  =  .9966358
7._at: AC_mc =  1.182642
       R_mc  = -.9966358
8._at: AC_mc =  1.182642
       R_mc  =         0
9._at: AC_mc =  1.182642
       R_mc  =  .9966358
```

_at	Margin	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
1	4.738983	.0681824	69.50	0.000	4.604492	4.873475
2	5.454491	.0707922	77.05	0.000	5.314851	5.59413
3	6.169998	.108964	56.62	0.000	5.955063	6.384933
4	5.013107	.0789537	63.49	0.000	4.857368	5.168845
5	5.621644	.0491713	114.33	0.000	5.524653	5.718636
6	6.230182	.0691667	90.07	0.000	6.093749	6.366615
7	5.28723	.1316386	40.16	0.000	5.027569	5.546891
8	5.788798	.0737851	78.45	0.000	5.643255	5.934342
9	6.290366	.0745807	84.34	0.000	6.143254	6.437479

From the plot visualization, I find that at 1sd above the mean of R (green line), the conditional effect slope is less positive, whereas, at 1sd below the mean (blue line), the conditional effect is more pronounced with a higher positive slope between the asset criticality and IoT Solution adoption.

iii. Variance inflation factor (VIF)

Variance inflation factor (VIF) for moderated multiple regression is investigated for collinear variables. It identifies the correlation between the IVs and the strength of the correlation. The output table below contains the VIF and tolerance – 1/VIF for each variable in the model.

Figure 39

Interaction of R on AC and ISA – Variance inflation factor (VIF)

Variable	VIF	1/VIF
AC	26.01	0.038452
R	12.81	0.078041
c.AC#c.R	54.80	0.018248
Mean VIF	31.21	

	ISA	AC	R	interact
ISA	1.0000			
AC	0.5119 0.0000	1.0000		
R	0.7542 0.0000	0.5295 0.0000	1.0000	
interact	0.6705 0.0000	0.9120 0.0000	0.8115 0.0000	1.0000

The threshold for a VIF value over 10 indicates multicollinearity (Hair et al., 1995, O'Brien, 2007). The VIF value for the interaction term AC*R at 54.8 indicates collinearity with AC and R. The tolerance is 1-R-square from the model where predictor AC*R is regressed onto the remaining predictors of AC and R. The remaining predictors in the model account for (1-0.0182)*100% = 98.18% of the variation in the interaction term.

Multicollinearity in the model is of structural type, i.e., the interaction term is created using other variables. The interaction term is a by-product of the model itself. The interaction term can thus be responsible for the high VIFs. The IVs and the interaction terms include the main effect and produce high multicollinearity. To reduce the structural multicollinearity, mean centring of the variables process is used (Auginis & Gottfredson, 2010, Jim Frost-webpage). The means of AC and R are subtracted from the observed values and divided by the variable's standard deviation. The VIF values were obtained per the table below using the centred variables.

Figure 40

Interaction of R on AC and ISA – mean centred variance inflation factor (VIF)

Variable	VIF	1/VIF
AC_mc	1.40	0.712553
R_mc	1.54	0.647782
c.AC_mc# c.R_mc	1.12	0.893594
Mean VIF	1.36	

	ISA	AC_mc	R_mc	interact
ISA	1.0000			
AC_mc	0.5119 0.0000	1.0000		
R_mc	0.7542 0.0000	0.5295 0.0000	1.0000	
interact	-0.3413 0.0000	-0.0857 0.2347	-0.3124 0.0000	1.0000

By removing the structural multicollinearity, VIF values indicate some multicollinearity, but it is not severe enough to warrant corrective measures. The centred model's coefficient and statistical significance will remain the same as the original model (Hayes, 2018). Per Hayes, any effect of centring on the standard error for the interaction term is counterbalanced by a corresponding change in the variance associated with the product term. Standard error and the test results are the same for the interaction term prior to and following the mean centring.

The tolerance is 1-R-square from the model where predictor AC*R is regressed onto the remaining predictors of AC and R. The remaining predictors in the model account for (1-0.894)*100% = 10.6% of the variation in the interaction term.

iv. Summary

Table 9

AC,R – Summary of test results

Goodness of Fit				
Relative Chi-Square	Kline, 1998	up to 3	3.06	Near Acceptable limit
Comparative fit index (CFI)	Byrne, 1994	up to 0.9	0.899	Near Acceptable limit
Non-normed fit index (NNFI) / Tucker-Lewis Index (TLI)	Byrne, 1994	up to 0.90	0.882	Near Acceptable limit
Standardized root mean square residual (SRMR)	Pituch & Stevens, 2016	up to 0.1	0.080	Close-fitting model
Coefficient of determination (CD)	Pituch & Stevens, 2016	close to 1	0.982	Close-fitting model
Significance Test for Moderation				
Without interacting effect		p-value		
Asset Criticality (AC)	Hayes, 2018	< 0.05	0.005	Statistically Significant
Responsiveness (R)	Hayes, 2018	< 0.05	0.000	Statistically Significant
With interacting effect		p-value		
Asset Criticality (AC)	Hayes, 2018	< 0.05	0.002	Statistically Significant
Responsiveness (R)	Hayes, 2018	< 0.05	0.000	Statistically Significant
Interacting Term - ACXR	Hayes, 2019	< 0.05	0.007	Statistically Significant
Variance inflation factor (VIF)				
Interacting Term – ACXR (mean-centered)	Hair et al., 1995	< 10	1.12	Inconsequential collinearity

The residuals test indicates that the model is close-fitting, and the fit indexes are near acceptable limits. The significance test indicates a statistically significant relationship with the interacting effect. The VFI (mean-centred) shows inconsequential collinearity. The difference in R-square between the two regression models – one with and another without interaction effect shows that responsiveness is moderating the relationship between asset criticality and IoT Solutions adoption; it is contributing significantly to the model (1.56%) and is statistically significant ($p<0.05$).

I find support for the moderating hypothesis, i.e., responsiveness of IoT Solution provider strengthen the relationship between asset criticality and adoption of IoT Solution (positive relation).

5.3 Analytic Intelligence

Automation in the industry to improve productivity, reduce mean time between repairs and failure, and improve quality and safety has been used for many years. Technologies to control production, operation and failures have been in use. However, these control technologies are contained within the manufacturing environment where they are used and depend on in-house expertise supplemented by manufacturers. With the advent of the internet, innovative solutions are emerging to enhance capital equipment performance by providing online and real-time inputs to plant operators. The solutions are still evolving. Depending on the requirements, locations, and needs of customers/users, the solutions are tailored to meet the requirements and expectations. From the basic level of monitoring the health of the equipment to providing signals for preventive maintenance, the solutions are becoming more advanced and complex. The solutions are offered by analyzing the data collected using the internet from the user's equipment by the service providers. From monitoring and real-time warning signals, the service providers are working to offer predictive and prescriptive intelligence to the users for better planning, coordination, and execution of business plans. The interviews of SMEs (subject matter experts) revealed that the user expects to move to predictive and prescriptive intelligence from IoT Solutions suppliers; however, there is still much work to be done at IoT Solutions providers end to prove the capabilities and raise the confidence of the user to move to such solutions.

Accordingly, the measure is developed basis the first-order concepts derived from such insights on analytics intelligence. The measures are tested for reliability and construct validity of the scale.

a) Construct Robustness

- A **reliability test** on the measure for the construct in the affective domain showed Cronbach's alpha coefficients of Analytic Intelligence (0.8984) to be higher than the threshold of 0.7, recommended by Nunnally (1978) for the test of scale reliability. As a measure of internal consistency, Cronbach's alpha value of analytic intelligence shows that the items forming the variable are closely related.
- **Average interitem correlations** of the items should be roughly the same and cluster narrowly. The average inter-item correlation of the Items measuring asset criticality ranges from 0.59 to 0.60 (the average inter-item correlation of asset criticality is 0.5959), indicating that all the items are correlated and fitted.
- For convergent validity, the **average variance extracted** (AVE) and composite reliability (CR) is examined based on the criterion of Fornell-Larcker (1981). AVE measures the ratio of variance captured by a construct versus the level due to measurement error. Standardized loading estimates of the times 0.5 or higher show convergent validity. The AVE values for analytic intelligence (0.596) have an AVE value above 0.5, indicating adequate convergent validity.

- The **composite reliability** (CR) is expected to have a value of 0.7 or higher. The CR values for asset criticality (0.8985 have a CR value above 0.7, indicating adequate internal consistency or convergence.

Table 10

ATI – Construct Robustness

Analytics	Factor Loading	AVE	CR	Average interitem Correlation	Cronbach's Alpha
Availability	0.7489			0.6029	
Life Cycle Cost	0.7814			0.5928	
Factory Productivity	0.7798	0.5960	0.8985	0.5937	0.8984
Customer Service	0.7677			0.5967	
Quality of product	0.7631			0.5988	
Safety of workers/operations	0.7906			0.5902	

- The **discriminant validity** is examined by finding the square root of the AVE and testing its value to be greater than the inter-item correlation (Fornell & Larcker, 1981)

Table 11

ATI – Discriminant Validity

Analytic Intelligence		q11_1	q11_2	q11_3	q11_4	q11_5	q11_6
Availability	q11_1	0.772					
Life Cycle Cost	q11_2	0.6202	0.772				
Factory Productivity	q11_3	0.5668	0.6259	0.772			
Customer Service	q11_4	0.5877	0.5597	0.6224	0.772		
Quality of product	q11_5	0.5595	0.5811	0.5736	0.6053	0.772	
Safety of workers/operations	q11_6	0.5743	0.6227	0.6124	0.5957	0.6306	0.772

(Square root of the AVE~0.596=0.7238 is indicated in the cells highlighted in yellow)

The testing above demonstrates satisfactory convergent and divergent validity of the items for asset criticality and responsiveness constructs.

b) Model Testing

Analytic Intelligence (ATI) is hypothesized to have a positive and direct relationship with IoT Solutions Adoption (ISA). The relationship is investigated analytically and tested for analytic intelligence's influence on IoT Solutions Adoption.

i. The goodness of fit

The likelihood ratio for the model vs the saturated model, the chi2 $\varkappa 2$ (53) = 123.63, prob>Chi2 = 0.000. The relative chi-square or the normed chi-square (chi-square index divided by the degree of freedom) is 2.33. The comparative fit index (CFI) is 0.952, and Tucker-Lewis Index (TLI), also known as the non-normed fit index (NNFI), is 0.94. The two incremental fit indices should be near zero and preferably more than 0.9 to indicate that the model is acceptable (Byrne, 1994). The standardized root mean square residual (SRMR) for a perfect fit corresponds to 0. A good fit model corresponds to a small value, limited to 0.05 for a close-fitting model and up to 0.1 for an acceptable fit (Pituch & Stevens, 2016). SRMR for the model with IC as a mediator is 0.040. The coefficient of determination (CD) is like an R^2 for the whole model, with a value close to 1 indicating a good model fit. CD for the model is 0.935, indicating an acceptable fit. The CFI/TLI values are near the threshold limits, whereas the residuals indicate a good fit; hence I continue to test the model for statistical significance.

Figure 41

ATI on ISA – Goodness of Fit

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(53)	123.634	model vs. saturated
p > chi2	0.000	
chi2_bs(66)	1525.057	baseline vs. saturated
p > chi2	0.000	
Baseline comparison		
CFI	0.952	Comparative fit index
TLI	0.940	Tucker-Lewis index
Size of residuals		
SRMR	0.040	Standardized root mean squared residual
CD	0.935	Coefficient of determination

ii. Significance Test

The regression model for the relationship between analytic Intelligence responsiveness with IoT solutions adoption (ISA) respectively indicates the relationships to be positive and statistically significant ($p<0.05$).

Figure 42

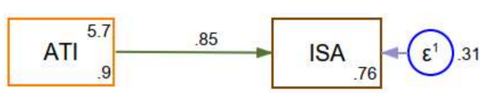
ATI on ISA – Regression coefficients

	(1) ISA
ATI	0.846***
	(19.98)
_cons	0.765**
	(3.14)
N	194
df_m	1
df_r	192
F	399.3
r2	0.675
rmse	0.559

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 43

ATI on ISA – model with coefficients



Model Specification - $\hat{y} = (0.765)\beta 0 + (0.846)\beta 1\ (ATI)$

Following the assessment and testing of the model for –

- The goodness of fit
- Significance test for mediation

I find support for the hypothesis, i.e., analytic Intelligence positively impacts the adoption of IoTS solutions.

6. Discussion

Research in trust, leadership, data & network security is widely available for adopting new technologies. Despite its perceived advantages, a large segment of industrial markets still finds it challenging to implement extensive IoT Solutions. Multiple challenges prevent the leap of faith from the Proof of Concept (POC)/ deployment stage to adoption and implementation (Tornatzky et al., 1990). This study's key objective is to identify and evaluate factors beyond the existing research influencing the adoption of IoT Solutions in the B2B market for capital goods in a pervasive way. Aligning the requirements of the users, Original Equipment Suppliers (OEMs), and service providers in the industry are key to the adoption.

Users of the capital goods in the industry are interested in having a complete IoT solution for the entire operation. Interoperability from the device level to the platform and domain level would help users reduce the implementation cost and the risk of vendor lock-in.

At the component level of analysis, I find that the direct effect of interoperability for the adoption of IoT solutions is significant. This finding is in line with the observation by (Bröring et al., 2017) that lack of interoperability is a serious entry barrier preventing the emergence of the IoT ecosystem. This study forwards the concept by identifying the factors that would be affected by interoperability leading to the adoption of IoT Solutions. I find empirical evidence that interoperability facilitates the reduction in the implementation cost of IoT Solutions, which in turn influences the increase in adoption of IoT Solutions. The indirect effect of the implementation cost of IoT Solutions is significant.

At the component level, the indirect effect of vendor lock-in mediating the relationship between interoperability and adoption of IoT Solutions is larger than the implementation costs. This study forwards the concept of Noura et al., 2019 that a lack of interoperability leads to vendor lock-in. This study identifies vendor lock-in as a causal link affecting the adoption of IoT solutions due to interoperability and quantitatively finds the indirect effect of the mediation.

At the supracomponent level, evidence is found of multi-mediation by reduction of implementation cost and vendor lock-in through interoperability, causing an increase in the adoption of IoT Solutions. When Implementation costs and Vendor lock-in enter the relationship between interoperability and IoT Solution adoption, the direct effect is reduced, providing evidence of partial mediation.

One of the factors in the decision to adopt IoT Solutions by the users is whether to implement them on all the equipment and machinery in the plant/operation or only on equipment critical for operation and safety. Criticality is the measure of risk associated with an asset (SWEFC). IoT Solution implementation enabling remote monitoring intends to improve the availability of assets (Oliva and Kallenberg, 2003), thereby reducing the risks for the users. Since this innovative technology is still going through pilot projects and proof of concepts, there is relatively less evidence of its utility under all applications in different industries. Hence some users interviewed were of the view to apply it to non-critical assets first and, after gaining confidence, can apply it to the critical assets. The users' confidence is affected positively if the IoT Service provider is highly responsive. The service provider's responsiveness moderates the relationship between asset criticality and IoT Solution adoption. At the individual component level, responsiveness and asset criticality were significant, with responsiveness predicting larger variation in IoT Solution adoption when holding asset criticality constant. The test for interaction is statistically significant, showing the evidence that the effect of asset criticality on IoT Solutions adoption is conditional on the level of responsiveness. Overall, the conditional effect of asset criticality on IoT Solutions Adoption becomes less positive as we move from lower levels of responsiveness to higher levels of responsiveness.

The ultimate goal of users operating the equipment/machinery is to run it at the most optimum condition, reliably, safely, meeting the quality requirements, and at the lowest cost. Users need feedback and intelligent analysis from the asset's measured parameters to enable them to meet their goals. It helps users reduce failure or unscheduled maintenance needs, which are more expensive than predictive or preventive maintenance (Wu et al., 2017, Lee et al., 2014, Zhang et al., 2013). The higher the level of intelligence, the greater the benefit for the user and the higher the adoption of IoT Solutions that provide intelligence to the user to meet their objectives. I find a positive and significant relationship between the analytic intelligence provided by IoT Solutions to the users and their intent to adopt it.

To summarize, the role of interoperability, asset criticality, and analytics intelligence in adopting IoT Solutions and their relationship is identified and assessed. In the process, I evaluated the causal links between implementation costs and vendor lock-in between IoT Solutions' adoption and interoperability. As the cost of implementation reduces due to interoperability and the user does not feel locked in by the supplier or service provider with a solution, the adoption of IoT Solutions will be positively affected. Analytic intelligence will allow the user to meet the objective of running the equipment in optimum condition and hence the adoption of the IoT Solution. Finally, if the asset is critical, it will have a high probability of being considered for implementation of the IoT Solution, and this would be aided if the solution provider is responsive.

6a Managerial Implications

Industrial B2B markets implemented instrumentation, controls, and automation solutions (ICA) a few decades back but have mostly remained in the proof of concept/pilot project stage when implementing IoT Solutions. Industrial operations are complex, and expenses undergo rigorous evaluation by multiple stakeholders before they are apportioned. Adopting new technologies for performance improvement in existing operational units is even more difficult as changes with no or minimal disruptions are the requirement. New technologies need to be proven for their reliability and the said benefits. The risks of failure and its implication are to be avoided. At the same time, the suppliers developing and implementing new technologies want revenue streams and profits for their efforts. This research is grounded on these significant practical challenges related to adopting IoT Solutions for capital goods in industrial markets.

The users value the analytic intelligence provided by OEM’s / service providers as it complements their people's skill sets and provides them with real-time inputs to make intelligent decisions that help keep their operations running optimally. Current predictive analytic intelligence based on historical data, trend lines, and event-based analysis helps users to identify the root cause and resolve issues to avoid future failures. Prescriptive analytic intelligence is in a nascent stage, and OEMs / service providers are developing such skills to provide the users' inputs that can help them to plan their activities like maintenance and maximize the remaining useful life (RUL) of components and equipment, thereby reducing the overall lifecycle cost of the capital goods installed. Users identify it as the maximum benefit for their operations and would be more likely to adopt IoT Solutions subscription on the availability of such intelligence.

User organizations need multiple capital equipment to operate synchronously for optimum performance. This can be better achieved if the control solutions for the capital equipment can communicate with each other, understand, and become autonomous. These capabilities can be obtained through the interoperability of the platforms, which not only helps users to manage the plant operations better but also help reduce the adoption and implementation costs. The OEM’s and service providers' goal should be to help reduce the implementation costs for the users, which can bring through interoperability of the devices up to the platform level.

Users are wary of being lock-in by the vendors as it restricts their ability to switch to another vendor in case of non-performance from the current supplier. Replacing a vendor without a substantial cost impact in the industrial setup is difficult, especially when a lock-in condition prevails. Interoperability reduces the vendor lock-in effect for the users and, in turn, creates confidence in the users to implement the IoT solutions.

Industrial companies have a gamut of capital equipment installed in their plant. However, all the equipment is not equally critical for the plant's performance. Some equipment has spare units installed which can operate during downtime or maintenance. Similarly, some equipment installed is for utilities. The criticality of the equipment varies, depending on the impact that it may have should it fail to operate. This study found a weak relationship between asset criticality and the adoption of IoT Solutions. However, the study shows that OEM/service provider responsiveness has a higher value for the customers in their decision to implement IoT Solutions. Firms should focus on responsiveness rather than segment by asset type to implement IoT Solutions.

6b imitations and Directions for Further Research

This study is focused on the factors that can move the industrial firms in the B2B market from the development and deployment phase to the adoption and implementation phase of technological innovation, i.e., IoT Solutions It focuses on factors pertinent at the firm level, whether it is the user, supplier, or service provider. Several key factors beyond the scope of this research, like government policies and infrastructure at the country level, are left for future investigations. Efforts are being made at international agency levels where multiple industries and government consortiums, councils, and governance forums are working to establish uniform policies and standards to benefit from interoperability. The impact of such efforts in getting uniform standards and how the firms will respond will be a case for further studies.

Implementing IoT solutions enabled by internet connectivity depends on the infrastructure available at the individual country level. Governments provide policy-level support and incentives to create, maintain and develop an environment and an ecosystem to support new technologies. Further investigation on the factors and indicators, like GDP and grouping of countries like ASEAN, BRICS, EU, and COMESA, play in motivating government policies and incentives to support IT infrastructure that is a foundational requirement for the firms to use.

At the industry level, further investigation is required to identify whether a particular industry is more open to adoption than others. Process industries that operate on a 24X7 basis versus manufacturing units that operate on one or two shifts a day – will they have the same propensity for adopting IoT Solutions? What traits of an industry type will indicate the degree of propensity to adopt IoT Solutions remains to be investigated.

At the firm level, further investigation is required to identify the differences, if any, between the adoption behavior of the firms that are going for a completely new project compared to the firms that are in operation and have to implement the new technologies as an improvement or an upgrade.

7. Conclusion

This research aims to uncover the constituents that customers, OEMs, and service providers can associate with and influence IoT Solutions' adoption in the B2B market for capital goods. The research proposes and tests the framework for adopting IoT Solutions in industrial markets that use operational technologies (OT) for control and automation but have not embraced the IoT solutions for their benefits in an efficacious pervasive way.

A theoretical model is designed based on my observations, literature review, and qualitative analysis from the interviews conducted with the subject matter experts as users, suppliers, or service providers for IoT Solutions. New constructs of Analytic Intelligence, Interoperability, implementation cost, vendor lock-in, and asset criticality were tested for reliability and validity. The data to test the constructs is obtained through an anonymous online survey from 194 participants from the industrial countries of ASEAN, India, China, Japan, and the USA.

Past research has looked at the factors influencing the adoption of new technologies, emerging technologies & challenges like data ownership and security that affect the adoption, or behavioral aspects like trust, organization culture, and leadership commitment. This study contrasts the earlier research by identifying and evaluating the factors that benefit the entire business chain, from the OEMs, service providers, and customers, influencing the adoption of IoT solutions.

The measurement model validation established the robustness of the proposed model. The results from the data analysis provide evidence of the relationship between the model constructs and their strength, as summarized in the table below.

Table 12

Summary of Hypothesis Testing

Hypothesis	Decision	Direction	Strength of Relation	Unstandardised correlation coefficient
H1 – Interoperability has a positive and direct impact on the adoption of IoT Solutions	Supported	Positive	Strong	0.71
H2 – Implementation cost of IoT Solutions mediates the relationship between interoperability and adoption of IoT Solutions	Supported	Positive	Moderate	Indirect effect of 0.139
H2a – Interoperability has a negative impact on the implementation costs of IoT Solutions	Supported	Negative	Moderate	-0.635
H2b — Lower the cost of implementing IoT Solutions, higher will be the adoption of IoT solutions.	Supported	Negative	Moderate	-0.53
H3 – Vendor Lock-in effect from proprietary IoT Solutions mediates the relationship between interoperability and adoption of IoT Solutions	Supported	Positive	Moderate	Indirect effect of 0.16
H3a - Interoperability has a negative effect on the vendor lock-in from proprietary IoT Solutions	Supported	Negative	Moderate	-0.612
H3b – Lower the vendor lock-in effect of proprietary solutions higher will be the adoption of IoT solutions	Supported	Negative	Moderate	-0.56
H4 – Criticality of an asset in an organization's operations positively influences the adoption of IoT Solutions.	Supported	Positive	Weak	0.42
H4a – Responsiveness of IoT Solution provider strengthen the relationship between asset criticality and adoption of IoT Solution	Supported	Positive	Weak	0.06
H5 – Analytic Intelligence has a positive impact on the adoption of IoTS solutions.	Supported	Positive	Strong	0.84

** Responsiveness of IoT Solution provider positively influence the adoption of IoT Solution - this relation is found to be strong with Pearsons Correlation Coefficient of 0.74

The model can be a starting point for the firms to formulate their strategies, utilize the value from the factors that are seen as important and apply it for mutual benefits. In addition to providing the empirical validation of the proposed model grounded on innovation adoption frameworks, this study provides direction for researchers for future studies in the industrial B2B markets in this focus area of the adoption and implementation of the potential benefits from IoT Solutions.

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9. Appendix

Appendix A Survey Questionnaire

		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
	Based on your experience, please indicate the response that most closely describes the degree of importance on a scale of 1 to 7, with (1) being Strongly disagree, (2) Disagree (3) Disagree Somewhat (4) Neither Agree nor Disagree (5) Somewhat Agree (6) Agree and (7) Strongly Agree.	1	2	3	4	5	6	7
6	*Think of interoperability as the ability of two or more IoT devices, systems, applications or platforms to communicate, exchange information and use it. I believe* ***interoperability is high*** *when...*							
	devices from different types/suppliers can communicate with each other on a platform							
	data can be seamlessly routed from wireless and wired instruments **over the network for end-to-end communication**.							
	data from the sender can be **correctly comprehended** by the receiver without any mismatch							
	data can be transferred **independent of the Operating system**							
	information can be exchanged seamlessly **between IoT platform and my companies internal systems like ERP, CRM** (Customer Relationship Management) and BPM (Business process management) applications.							
7	*Think about the various types of costs and their impact on the decision to implement an IoT Solution*							
	Hardware devices like sensors, routers, gateways, upgrading/modification of servers, and storage capacity are high costs of implementing IoT solutions.							
	Software license, customization, and software modification for compatibility are high costs of implementing IoT solutions.							
	Services Costs like external consulting fees, training of employees, cloud service and insurance premium							
	Data Integration costs from different software's/platform							
	Operating Costs like Subscription fees, maintenance costs							
8	*Think about the dependence on the Solution provider that users may encounter when implementing an IoT Solution*							
	Most of the IoT Solutions available are **proprietary**, incompatible with other providers and prevent integration onto one platform							
	There is a **lack of industry standards** on IoT Solutions to allow changing suppliers/service providers easily							
	For **critical equipment**, proprietary IoT solution from vendors is acceptable due to their expertise in their supplies, product and services.							
	For **non-critical equipment**, a proprietary IoT solution is acceptable							

9 *Think about the machinery/equipment that is considered as Critical by the user. Based on it, a Critical equipment is any equipment that*

affects the overall **production capacity** of the plant/factory							
affects the **safety** of operators in the plant							
has **no spare Unit/redundancy** available							
is customized for the requirement/supplied from a **monopoly** supplier and **requires's specialized knowledge**							
where we **lack in-house maintenance capability** of that particular equipment							
for which the supplier may not be able to provide a fast service response							
that has a **high first cost/ cost** of purchase							
that is a **bad actor/frequently failing**							

10 *Think of Responsiveness as the ability to respond quickly to requests and assist with problems. Please rate by the degree of importance the responsiveness requirement from IoT Solution Provider*

has fast, efficient procedures for providing inputs on key parameters							
typically meets our expectations for life cycle reliability							
Turnaround time for work performed typically meets our expectations for service delivery							
Service personnel competently handle most of our requests/queries							

11 *Please indicate your level of agreement with the statement on use of IoT solutions –*

Increase the **availability** ((% of time machine can be used) of equipment/machine							
Reduce overall life cycle cost (Buy cost + Operate and Maintenance Cost) of the equipment/machinery							
Increase the overall **plant/factory productivity**							
Enhances customer service							
Improve the quality of the product manufactured							
Improve the **safety** of the plant/operation and its people							

13 *Please indicate your level of agreement with the statement on use of IoT* ***Solutions*** *–*

The devices are easy to use							
The dashboard and reports are clear and easy to understand							
There is flexibility of setting up the analytic report per our requirement							

14 *Please indicate your level of agreement with the statements below*

I will explore opportunities to get better quality solution compared to the present available							
I would strongly recommend Organizations to use IoT Solutions							
I believe that adopting IoT Solutions have largely benefited organization							

Questions dropped from 14 - for statistical analysis							
I foresee reduction in usage of the IoT Solutions							
I foresee IoT Solutions industry to be stagnant for next 2 to 3 years							
I would prefer an IoT solution provider to provide services for the repair and maintenance of the equipment							