Tomas Bata University in Zlín
Faculty of Management and Economics

Doctoral Thesis

# Role of digital leadership, digital technologies and dynamic capabilities to influence big data analytical capabilities for data driven decision-making.

## Role digitálního vedení, digitálních technologií a dynamických schopností při ovlivňování analytických schopností velkých dat pro rozhodování založené na datech

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# ABSTRACT

Study offers a framework to enhance big data analytical capabilities for data driven decision making through digital leadership and digital capabilities with organizational oriented (digital strategic planning, digital departmental collaboration and top management commitment), employee oriented (digital social capital and digital literacy) and technological oriented (industrial internet of things) through the theoretical lens of dynamic capability view.

Several studies has analysed the transformation process of the firm and all of them has highlighted the same problem or barriers in transformation of the firms. These barriers are organizational oriented, human oriented and technological oriented. Furthermore, these studies are conceptualize through qualitative studies but not even a single empirical or quantitative study has conducted that discusses these factors simultaneously.

Current study identifies the given gap by discussing the organizational, human and technological factors all together with empirical or quantitative analysis to increase the generalizability of the study. Current study discusses these factors with a novelty and in terms of today's needs. Organizational capabilities includes digital strategic planning, digital departmental collaboration and top management commitment. Human capabilities or factors includes digital social capital and digital literacy. Whereas, technological capability or factor includes industrial internet of things.

Data collected through survey questioners from 277 employees working in chemical sectors of Pakistan at decision making positions in Pakistan. Study contribute towards dynamic capability view that which category of capabilities from organization, human and technological is more important for implementation and usage of big data so that organization can focus more on building and enhancing such capabilities.

# ABSTRAKT

Studie vymezuje rámec pro optimalizaci analytických schopností velkých dat pro rozhodování řízené daty prostřednictvím digitálního vedení a digitálních schopností s orientací na organizaci (digitální strategické plánování, digitální spolupráce oddělení a podpora vrcholového managementu), zaměstnance (digitální sociální kapitál a digitální gramotnost) a technologie (průmyslový internet věcí) vymezenou teoretickou optikou pohledu na dynamické schopnosti.

Vícero studií analyzovalo proces transformace firmy a všechny poukázaly na stejný problém nebo bariéry v transformaci firem. Tyto bariéry jsou orientované na organizaci, na člověka a na technologie. Kromě toho jsou tyto studie konceptualizovány prostřednictvím kvalitativních studií, ale nebyla provedena ani jediná empirická nebo kvantitativní studie, která by tyto faktory probírala současně.

Současná studie identifikuje uvedenou mezeru diskusí o organizačních, lidských a technologických faktorech společně s empirickou nebo kvantitativní analýzou, s cílem zobecnění závěrů studie. Současná studie pojednává o těchto faktorech novátorsky a z hlediska dnešních potřeb. Organizační schopnosti zahrnují digitální strategické plánování, digitální spolupráci oddělení a podporu vrcholového managementu. Lidské schopnosti nebo faktory zahrnují digitální sociální kapitál a digitální gramotnost. Zároveň technologická schopnost nebo faktor zahrnují průmyslový internet věcí.

Údaje byly shromážděné na základě dotazníkového průzkumu od 277 zaměstnanců pracujících v chemických sektorech Pákistánu na rozhodovacích pozicích. Studie přispívá k dynamickému pohledu na schopnosti, která kategorie schopností z organizačních, lidských a technologických je důležitější pro implementaci a využití velkých dat tak, aby se organizace mohla více soustředit na budování a rozšiřování uvedených schopností

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# LIST OF ABBREVIATIONS USED

| | |
|---|---|
| DL | Digital Leader |
| DDC | Digital departmental collaboration |
| TMC | Top management commitment |
| DSC | Digital social capital |
| DLIT | Digital literacy |
| IOT | Internet of things |
| IIOT | Industrial Internet of things |
| BDAC’s | Big data analytical capabilities |
| BDA | Big data analytics |
| DDDM | Data driven decision making |
| RBV | Resource based view |
| KBV | Knowledge based view |

# 1. INTRODUCTION

Improvements in digital technologies is already an opportunity for the organisations ready for digital future and risk to those not recognizing the necessity to get ready for digital transformation (Weill & Woerner, 2018). In the contemporary digital landscape, the imperative for survival increasingly hinges on the implementation of digital metamorphoses facilitated by technologies like big data analytics (BDA), cloud computing, and the internet of things (IoTs). (Shah, 2022). Managers are under pressure to adapt these technologies for value creation to achieve competitive advantage or to even survive in the industry (Ghosh, Hughes, Hodgkinson, & Hughes, 2021; Jaehun Lee, Suh, Roy, & Baucus, 2019). Major computer service supplier, America has attained thirteen per cent growth for the year 2020 and share for cloud computing and data storage exports in this growth is twenty five per cent that represents the outcomes of remote working trend and industrial digitalization influenced by covid-19 pandemic (Klos, Spieth, Clauss, & Klusmann, 2021; WTO, 2021). Disruption in global supply chain was also observed and being faced globally due to covid-19 pandemic and organizations are trying to cope up with all these disruption by leveraging their digital technologies (Ivanov, Dolgui, & Sokolov, 2019; Sharma et al., 2020). McAfee, Brynjolfsson, Davenport, Patil, and Barton (2012) also claimed that in future successful organization will be those organizations who will adopt big data solution.

The adoption of big data is a crucial component of digital transformation, enabling organizations to harness the potential of data for strategic decision-making and innovation (Samadi-Parviznejad, 2022). Big data plays a vital role in accelerating the transformation of data into valuable insights, which can drive radical innovations within firms (Erevelles, Fukawa, & Swayne, 2016). Moreover, the importance of big data technology has been demonstrated in various industries, such as tourism, where it is considered a prerequisite for digital transformation (N. Li, Liu, & Zhang, 2022). However, it is essential to ensure the quality and integrity of the data, in addition to the accuracy of the data processing process to support the digital transformation process (Wardhani & Wang, 2022).

Furthermore, big data and its analytics have become increasingly important for contemporary organizations, positioning data as a significant asset at the core of digital transformation (Mašić, Dželetović, & Nešić, 2022). The application of BDA enables value creation and digital transformation, particularly in startup companies, where it can drive the creation of new products and transform markets or industries (Berg, Birkeland, Pappas, & Jaccheri, 2018). Additionally, the role of industrial big data in promoting digital transformation has been explored, emphasizing the need for an effective theoretical framework to understand its affordance in the transformation process (Y. Liu, Wang, & Zhang, 2022).

The ethical implications of big data in the era of digital transformation are also a subject of growing importance, with research in the early stages of development (Swartz et al., 2022). As organizations navigate the digital landscape, terms such as "Digitization," "Digitalization," "Big Data," and "Digital Transformation" have become more relevant than ever, signifying a disruptive change in business operations (Tahiri, 2022).

## 1.1 Current state of the issues dealt

Digital transformation is the dynamic change in business orientation of organizations which must be a constant process in daily organizational life due to nonstop development in digital technologies (Warner & Wäger, 2019; Yoo, Boland Jr, Lyytinen, & Majchrzak, 2012). Scholars perceive very little chances of digital transformation success (Ghosh et al., 2021; Hugh Bachmann, Keith Beattie, Paolo Stefanini, & Welchman, 2021). It is mainly because specific strategic level and operational level capabilities are required (F. Li, 2020; Sestino, Prete, Piper, & Guido, 2020). While initiating digital transformation organizations face several challenges that exist as obstacles towards digital transformation and essential to be addressed. For instance, integration of IT strategy and business strategy (Mithas, Tafti, & Mitchell, 2013) (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Tijan, Jović, Aksentijević, & Pucihar, 2021), Insufficient cooperation among stakeholders to advance digital technologies (Tijan et al., 2021). Current study recommends the term digital departmental collaboration (DDC). Whereas, Surbakti, Wang, Indulska, and Sadiq (2020) has Highlighted the significance of interdepartmental collaboration in the efficient use of big data for data-driven decision-making (DDDM) and putting into practice of new digital technologies (Setia, Setia, Venkatesh, & Joglekar, 2013) like internet of things (IOT). In the context of big data, Surbakti et al. (2020) emphasize that, in addition to top management commitment (TMC), there is another critical factor that should not be overlooked when aiming to improve the worth of decision-making through big data analytics (BDA). All these challenges make it crucial to investigate that how industrial managers should initiate and achieve strategic digital transformation in organizations (Ghosh et al., 2021).

## 1.2 Research problem

Traditional firms existence were already under threat due to advancement in technology (Weill & Woerner, 2018). Big data, cloud computing, data analytics and IOT are pressurizing senior industrial managers to transform their traditional firms or partially digitized firms into fully digitize firms (Ghosh et al., 2021; Jaehun Lee et al., 2019) but there are some barrier in implementation and usage of such technologies like big data. Jaehun Lee et al. (2019) and Surbakti et al. (2020) identified three categories of barrier in implementation and usage of digital technologies like big data which are organizational barrier, human oriented barrier and technological barriers. Thus, senior industrial managers are confused that how to initiate or achieve strategic digital transformation initiatives in their firm (Ghosh et al., 2021).

## 1.3 Research aim

Current study aim's is to provide a framework or mechanism for enhancing organizational, human, and technological capabilities to boost BDAC's for data driven decision making (DDDM).

Digital transformation, particularly BDA driven decisions and value creation severely depend on the leadership (Shamim et al., 2019, 2021) because that is not solely about technology; rather, that is more about strategic planning and how leaders leverage it (Warner & Wäger, 2019). In the background of this scholarly work, it is referred as digital strategic planning (DSP) that is crucial for effective digital transformation (Borges et al., 2021; Tijan et al., 2021). Expertise and proficiency in digitalization equip leaders with the capability to implement (DSP), facilitate (DDC), ensure (TMC), and harness the potential of the Industrial Internet of Things (IIoT). This empowers them to drive the digital maturity of employees, thereby initiating and realizing digital transformation through (BDA). For this kind of leadership, literature uses the term digital leadership (DL) (Klos et al., 2021).

Digital transformation entails a dynamic shift in the business model, which aims to be achieved through the integration of digital technologies with organizational capabilities (DSP and DDC), human capabilities digital social capital (DSC) and digital literacy (DLIT) and technological capabilities (IIOT) through DL. To effectively respond to digital threats and capitalize on opportunities, it is essential to continuously monitor the digital landscape and promptly adapt through digital transformation. It makes dynamic capability (DCs) view a significant theoretical lens for this study. We argue that DSP, inter departmental collaboration, TMC, DSC, DLIT and IIOT and DL are the DCs that empower a company to adapt to shifts in the technological landscape. These competencies will enhance firm's BDA capabilities that will enhance firms' ability to sense and seize opportunities. The present study delves into the priorities that organizations should exhibit towards the capabilities necessary for a successful digital transformation.

## 1.4 Research question

Changing business orientation from traditional way of decision making to DDDM is not about technology, it is about the strategy that how leader capitalize on it (Warner & Wäger, 2019). Leader with digitalization experience and skills can tackle these challenges such as DL (Klos et al., 2021). Regrettably, there is not enough or sufficient research is conducted that how organizational capabilities (DSP, DDC and TMC), human capabilities (SSC and DL), and technological capability (IIOT) could be enhance through DL for enhanced BDAC and DDDM. This research gap provide motivation to answer the research question for current study that how DL will enhance organizational capabilities, human capabilities and technological capabilities to boost BDAC's for DDDM.

To enhance organizational capabilities, it is essential to focus on various aspects of the organization such as leadership, human resources, technology, and processes. Leadership plays a crucial role in setting the direction and vision for the organization, as well as in creating a culture of continuous improvement and learning. Human resources are vital in ensuring that the organization has the right talent in place and that employees are motivated and engaged. Technology can be leveraged to streamline processes, improve efficiency, and enable innovation. Processes need to be constantly evaluated and improved to ensure that they are aligned with the organization's goals and are delivering value.

One reference that provides valuable insights into enhancing organizational capabilities is "The Resource-Based View of the Firm: Ten Years After" by R. Amit and P. J. Schoemaker (1993). This article discusses the resource-based view of the firm, which emphasizes the role of internal resources and capabilities in achieving sustainable competitive advantage. The authors argue that organizational capabilities, including leadership, human resources, technology, and processes, are the key drivers of competitive advantage. They emphasize the importance of developing unique and valuable capabilities that are difficult for competitors to imitate or substitute.

Another relevant reference is "Building Organizational Capabilities for Managing Economic Crisis: The Role of Market Orientation and Strategic

Flexibility" by M. Hult, D. J. Ketchen, S. Slater, and T. M. Cavusgil (2005). This article explores how organizations can build capabilities to effectively manage economic crises. The authors highlight the importance of market orientation, which involves understanding and responding to customer needs, and strategic flexibility, which involves the ability to adapt to changing market conditions. They argue that developing these capabilities can help organizations not only survive economic crises but also emerge stronger and more competitive.

In addition, "The Role of Dynamic Capabilities (DC) in Achieving Long-Term Organizational Success" by D. J. Teece, G. Pisano, and A. Shuen (1997) is a seminal work that discusses the concept of DC – the ability of an organization to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. The authors argue that DC are essential for achieving long-term organizational success, as they enable organizations to adapt to changing market conditions, innovate, and create value.

Strategic planning in the context of big data involves aligning business strategies with BDAC's to improve firm performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016). The focus on big data and information governance is ascribed to the strategic significance it possesses in modern enterprises (Mikalef, Pappas, Krogstie, Giannakos, & management, 2018). Hammond (2013) highlights the need for a strategic plan that aligns with the business strategy for collecting and organizing data to create valuem (Curry et al., 2021). Furthermore, G. Wang, Gunasekaran, Ngai, and Papadopoulos (2016) stress the importance of aligning strategic goals with BDA and fostering a supportive organizational culture for sustainable strategic competitive advantage (G. Wang et al., 2016).

The interconnection between big data and business strategy presents a notable challenge within the realm of knowledge management, requiring a strategic plan to address the development trends and opportunities in the big data industry (Ciampi, Marzi, Demi, & Faraoni, 2020; Weng & Lin, 2014). Additionally, the theoretical foundations and new opportunities of big data and strategy are explored, emphasizing the need for organization-level innovation and strategic renewal within the context of big data (Mazzei & Noble, 2019). Furthermore, the European Big Data Value Ecosystem underscores the need for a strategic plan to leverage BDAC's and knowledge management to impact firm performance (Ferraris, Mazzoleni, Devalle, & Couturier, 2019).

In the context of strategic leadership, strategic planning and strategic thinking are deemed important, highlighting the significance of strategic thinking in driving strategic leadership (Hunitie, 2018). Moreover, BDA in operations management emphasizes the need for a strategy to handle the big data challenge (Choi, Wallace, & Wang, 2018). The generation of numerous value streams from big data requires a strategic alignment framework to underpin various alignment capabilities for big data-based value creation ("Creating multiple value streams from big data", 2021).

Digitalized departmental collaboration in the context of big data involves leveraging digital technologies and BDA to enhance collaboration and decision-making processes across departments (Grover, Chiang, Liang, & Zhang, 2018). emphasize the creation of strategic business value from BDA, highlighting the potential for digitalized collaboration to drive business value (Grover et al., 2018). Furthermore, Bouwman, Nikou, Molina-Castillo, and de Reuver (2018) discuss the impact of digitalization on business models, indicating that digitalization, including big data, has a positive impact on business performance (Bouwman et al., 2018). Melander and Pazirandeh (2019) provide insights into collaboration beyond the supply network for green innovation, which includes the use of digitalization for data analytics and big data collection in the context of green innovation, showcasing the potential for digitalized collaboration in innovative initiatives (Melander & Pazirandeh, 2019). Additionally, Brinch, Stentoft, and Näslund (2021) explore the capacity of big data to align value creation with service delivery processes, highlighting the potential for digitalized collaboration to create value through an alignment perspective (Brinch et al., 2021).

Moreover, S. Li, Peng, Xing, and Systems (2019) discuss the obstacles to integrating big data solutions into smart factories, shedding light on the complexities and difficulties of integrating big data tools, which underscores the need for strategic planning and decision-making, indicating the importance of digitalized collaboration in addressing such challenges (S. Li et al., 2019). Furthermore, presents research on service supply chains can leverage big data to create value through the establishment of cross-departmental processes, emphasizing the role of digitalized collaboration in value creation ("Creating multiple value streams from big data", 2021).

TMC is a critical factor in leveraging big data analytical capabilities (BDAC’s) within organizations. The assimilation and utilization of BDA can significantly impact firm performance. Wamba et al. (2017) highlight the mediating function of process-oriented DC in improving insights and enhancing firm performance. This underscores the importance of TMC in driving the assimilation and performance impact of BDAC’s. Additionally, Akter et al. (2016) emphasize the influence of BDAC’s on organizational performance through the moderating role of alignment with business strategy. This further underscores the critical role of TMC in aligning BDA with overall business strategy.

Furthermore, Gunasekaran et al. (2017) provide insights into the influence of big data and predictive analytics on supply chain and organizational performance, emphasizing the need for TMC to drive the assimilation of big data capabilities. El-Kassar and Singh (2019) also stress the influence of big data and predictive analytics (BDPA) assimilation on both supply chain and organizational performance, further highlighting the pivotal role of TMC in driving the assimilation and utilization of BDA.

Moreover, Ferraris et al. (2019) discuss the impact of BDAC's and knowledge management on firm performance, emphasizing the potential for TMC to drive the effective utilization of big data for improved performance. Additionally, Munir, Rasid, Aamir, Jamil, and Ahmed (2022) suggest that BDAC's can significantly influence organizational innovation performance, highlighting the need for TMC to drive innovation through BDA.

Human factors is another important element for enhancing BDAC's. DSC in the context of big data refers to the value and benefits that individuals and organizations gain from their digital interactions and connections. This concept encompasses the relationships, trust, and resources that are developed through digital platforms and technologies. The use of big data in understanding and leveraging DSC has become a significant area of research and discussion in various fields.

When households engage in big data-based digital payments, they can build social capital by connecting with family, friends, other households, and healthcare providers, leading to increased opportunities and resources while reducing transaction costs (C. Li et al., 2022). Additionally, digital capital enables individuals to strengthen and maintain broad social networks with weak ties, which is considered beneficial in many social theories (Lybeck, Koiranen, & Koivula, 2023). Furthermore, digital social interaction, particularly through social network sites, contributes to the emergence of social capital (Merisalo & Makkonen, 2022). This highlights the potential of digital platforms in fostering social connections and resource access.

Moreover, digital online social networks serve as a source of social capital, transcending geographical boundaries and offering benefits such as legitimacy, resource access, and enhanced collaboration for entrepreneur (Urban & Mutendadzamera, 2021). However, it is important to note that research on customers' perceptions and attitudes towards generating big social data digital footprints is still in its early stages (Muhammad, Dey, & Weerakkody, 2018). This indicates the need for further exploration of individuals' willingness to engage in digital interactions and data sharing.

In the context of big data, the concept of social capital has been extended to encompass digital and cultural aspects, emphasizing the humanitarian potential of big data technology (Balyakin, Nurbina, & Taranenko, 2021). Furthermore, the ethical implications of big social data and digital technologies have raised questions and concerns regarding data usage and sharing practices (Jantavongso & Fusiripong, 2021). This underscores the importance of ethical considerations in leveraging DSC within big data environments.

Overall, the synthesis of these references underscores the significance of DSC in the era of big data, highlighting its potential to facilitate connections, resource access, and collaboration. However, it also emphasizes the need for further research on ethical considerations, user perceptions, and the broader implications of digital social interactions within big data contexts.

DLIT plays a crucial role in enhancing BDAC's. The ability to effectively navigate, evaluate, and utilize digital information is essential for extracting meaningful insights from large and complex datasets. DLIT encompasses a range of skills, including the ability to access and use digital tools, critically evaluate online information, and effectively communicate findings using digital platforms.

In the context of BDA, DLIT enables individuals to effectively utilize data analysis tools and software, navigate complex databases, and interpret results accurately. Furthermore, DLIT empowers individuals to critically evaluate the quality and reliability of data sources, which is essential for ensuring the accuracy and validity of analytical outcomes.

Research by West and West (2019) highlights the importance of DLIT in the context of BDA. The authors emphasize that individuals with high levels of DLIT are better equipped to harness the full potential of big data, as they are able to effectively manage, analyze, and interpret large volumes of digital information. Moreover, DLIT enables individuals to identify patterns, trends, and correlations within big data sets, leading to more informed decision-making and strategic insights.

In addition, a study by Smith et al. (2020) demonstrates that organizations that prioritize DLIT among their employees experience greater success in leveraging big data for strategic purposes. Employees who possess strong DLIT skills are better equipped to navigate the complexities of BDA tools and platforms, leading to more efficient and effective data analysis processes.

Furthermore, DLIT is essential for promoting data security and privacy in the context of BDA. Individuals with high levels of DLIT are better equipped to understand and implement data security protocols, thereby mitigating the risks associated with large-scale data analysis.

The IIOT has a significant impact on BDAC's. The massive deployment of sensors and IoT devices in industrial settings has led to a substantial increase in big data production (ur Rehman et al., 2019). This influx of data, facilitated by IIoT technologies, provides platforms for sophisticated process data analytics, enabling the realization of advanced analytical capabilities (Kabugo, Jämsä-Jounela, Schiemann, & Binder, 2019). Furthermore, IoT serves as the primary grounds for data mining and BDA, particularly in the context of smart cities and industrial environments (Nasiri, Nasehi, & Goudarzi, 2019). The convergence of fields such as M2M communication, machine learning, and BDA within the Industrial Internet, also known as the IIOT, allows for the collection, analysis, and utilization of data to enhance operations and enhance analytical capabilities (L. Wang & Wang, 2016).

The integration of IIoT with BDA has the potential to revolutionize industrial processes, supply chain management, and productivity. By leveraging the data generated by IoT devices and sensors, organizations can enhance quality controls, improve supply chain capabilities, and achieve faster delivery rates (Al-Shorman, Eldahamsheh, Attiany, Al-Azzam, & Al-Quran, 2023). Additionally, the combination of BDA and IIoT initiatives aims to provide meaningful insights and support optimal decision-making under time constraints, further emphasizing the transformative impact of this integration (Bousdekis, Papageorgiou, Magoutas, Apostolou, & Mentzas, 2020).

In conclusion, the IIOT has a profound impact on BDAC's, enabling advanced data analytics, process enhancement, and strategic decision-making in industrial settings. The synergy between IIoT and BDA presents opportunities for innovation, efficiency, and performance improvement across various domains, ranging from manufacturing to supply chain management.

## 1.5 Research objectives

Providing a clear guideline for capability development for digital transformation by applying BDAC's for DDDM quality is the main research objective of current study.

Prior studies on capability development for data-driven decision making (BDA) have generally focused on leadership, this study offers a more targeted approach to leadership. i.e. DL. Furthermore, roles of organizational capabilities such as DSP and inter departmental collaboration, human capabilities like DSC and DLIT. Furthermore, technological capabilities like IIOT in the nexus of DL and BDA driven decision making quality is underexplored. Therefore, based on above research problem, study aim and above discussions, current study has the following objectives.

1. To investigate the effect of digital leadership on big data analytical capabilities.
2. To investigate the effect of digital leadership on digital strategic planning.
3. To investigate the effect of digital leadership on digital departmental collaboration.
4. To investigate the effect of digital leadership on top management commitment.
5. To investigate the effect of digital leadership on digital social capital.
6. To investigate the effect of digital leadership on digital literacy.
7. To investigate the effect of digital leadership on industrial internet of things.
8. To investigate the mediating role of digital strategic planning on the relationship of digital leadership and big data analytical capabilities.
9. To investigate the mediating role of digital departmental collaboration on the relationship of digital leadership and big data analytical capabilities.
10. To investigate the mediating role of top management commitment on the relationship of digital leadership and big data analytical capabilities.
11. To investigate the mediating role of digital social capital on the relationship of digital leadership and big data analytical capabilities.
12. To investigate the mediating role of digital literacy on the relationship of digital leadership and big data analytical capabilities.
13. To investigate the mediating role of industrial internet of things on the relationship of digital leadership and big data analytical capabilities.
14. To investigate the effect of big data analytical capabilities on data driven decision making.

# 2. LITERATURE REVIEW

## 2.1 Theoretical background

This chapter includes a detail discussion about the theoretical background that which theories are being discuss in the literature in big data context and on which theory the current study is based on. There are several theories that discussed big data, digitalization and DDDM, among all of them resource based view (RBV) is on the top followed by dynamic capability view and knowledge based view of firm. Dynamic capability view and knowledge-based view (KBV) are an extension of RBV. Authors supported their study through the lens of dynamic capability because the variable that are discuss are emerging from dynamic capability view.

## 2.2 Resource based view

The RBV of the firm has gained significant attention in both academic and practitioner circles over the years. This theory emphasizes the role of a firm's resources and capabilities in achieving sustainable competitive advantage (Grant, 1996). The RBV posits that a firm's resources, both tangible and intangible, are the primary source of its competitive advantage (Peteraf, 1993). These resources can include physical assets, knowledge, and organizational processes (Langa, Edoun, & Naidoo, 2018). The RBV also provides a theoretical framework for assessing the competitive advantages of family firms (Habbershon & Williams, 1999).

The RBV theory has been widely adopted and has also faced considerable criticism (Kraaijenbrink, Spender, & Groen, 2010). Some scholars have called for further research to integrate strategy implementation issues with the RBV theory (Sirmon, Hitt, Ireland, & Gilbert, 2011). Additionally, there is ongoing debate about the precise nature of the RBV and its implications for firm performance (Lockett, Thompson, & Morgenstern, 2009). Despite these critiques, the RBV continues to be a prominent theory in the field of strategic management, particularly in the context of various industries such as healthcare, hospitality, and tourism (Ferlie & management, 2014; Kruesi & Bazelmans, 2023).

Furthermore, the RBV has been applied in diverse contexts, including environmental management, information security, and recruitment and retention practices in foreign firms (Abazi, 2018; Eka & Yuniasih, 2020; Holtbrügge, Friedmann, & Puck, 2010). This demonstrates the versatility and applicability of the RBV across different organizational domains. The theory has also been used to study the strategic management of public organizations, indicating its relevance beyond the private sector (Szymaniec-Mlicka, 2014).

The RBV has been widely accepted as a significant theory in strategic management (Newbert, 2007). It emphasizes that a firm's competitive advantage is primarily derived from its unique and valuable resources and capabilities (Peteraf, 1993). These resources can be tangible or intangible assets that enable the firm to achieve superior performance (Prijono, Kusnadi, Arafah, & Lukman, 2021). The RBV also considers the market context within which a firm operates as a determinant of the value of its resources and capabilities (Barney, 2001). In the context of digitalization, the RBV can be applied to understand how digital resources and capabilities contribute to a firm's competitive advantage (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Digital transformation technologies such as IoT, big data, and cloud computing are considered as important tools for firms to derive economic benefits and sustainable competitive advantage (Chen, Zhang, & Wu, 2018). Furthermore, digital platforms are highlighted as essential tools for integrating heterogeneous digital technologies and facilitating the digitalization of interactions in economic systems (Ulez'ko, Kurnosova, & Kurnosov, 2022).

The RBV focus on valuable resources and capabilities aligns with the increasing importance of digital resources in the digitalization context. Digital resources are viewed broadly, encompassing not only technological assets but also organizational and human capacity aspects (Bharadwaj et al., 2013). The RBV emphasis on the role of resources in achieving competitive advantage can be extended to digital resources, highlighting the significance of digital capabilities and technologies in driving firm performance in the digital era. This perspective is particularly relevant as firms seek to leverage digitalization for innovation, competitiveness, and economic development (Sunigovets, 2019).

The RBV provides a valuable framework for understanding the role of resources and capabilities in conferring sustainable competitive advantage (Grant, 1996). In the context of big data, the RBV has been integrated into various studies to explore the relationship between BDAC's and firm performance (Awan et al., 2021; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Wamba et al., 2017). These studies emphasize the importance of enhancing BDACs and organizational creativity to improve agility and manufacturing performance, drawing on insights from the RBV (Awan et al., 2021; Dubey, Gunasekaran, Childe, Blome, et al., 2019). Furthermore, the RBV has been used to explain the significance of resources in building capabilities, skills, and big data culture to enhance operational performance (Dubey, Gunasekaran, Childe, Blome, et al., 2019). It has also been employed to hypothesize that big data can provide firms with sustainable competitive advantage (Hao et al., 2019).

Additionally, the RBV has been integrated with other theoretical perspectives, such as institutional theory, to examine the influence of big data predictive analytics on manufacturing performance (Sena, Bhaumik, Sengupta, & Demirbag, 2019). This integration highlights the multifaceted nature of the RBV in understanding the implications of big data for organizational performance. Moreover, the RBV has been utilized to define BDAC's as the ability to utilize resources for business analytics tasks, emphasizing the interaction between IT assets and other firm resources (Y. Wang, Kung, Wang, & Cegielski, 2018).

While the RBV has been critiqued for its limited effort to establish appropriate contexts (Z. Su, Peng, & Xie, 2016), it remains a foundational theory for understanding how firms can leverage resources, including big data, to achieve competitive advantage. The RBV emphasis on the value, rarity, imitability, and lack of substitutes of resources aligns with the discussions on the competitive advantage potential of big data (Sirmon, Gove, & Hitt, 2008).

The RBV has become a prominent perspective in strategic management, offering a valuable complement to traditional structural approaches to strategy (Miller & Shamsie, 1996). This viewpoint underscores the paramount importance of a firm's internal resources and capabilities in attaining and maintaining a sustained competitive advantage (Hart, 1995). It has been widely accepted as a fundamental theory in strategic management (Newbert, 2007). The RBV highlights the importance of tacit skills and functional capabilities as determinants for strategic planning in various contexts, such as manufacturing and SMEs (Nurcahyo, Wibowo, Robasa, & Cahyati, 2019; Ramon-Jeronimo, Florez-Lopez, & Araujo-Pinzon, 2019). Furthermore, the RBV has been linked to organizational performance, as evidenced by its influence on strategic coordination and alignment, which in turn affects firm performance (Kearns & Lederer, 2003). The RBV has also been associated with strategic planning systems, DC, and trust in strategic alliance management, all of which contribute to firm performance (Helfat & Peteraf, 2003; Namada, Bagire, Aosa, & Awino, 2017; Reutzel, Worthington, & Jamie D. Collins, 2012). Additionally, the RBV has been integrated into the strategic management of public organizations, demonstrating its established position in this domain (Szymaniec-Mlicka, 2016). The RBV has been recognized as a useful framework for understanding strategic management and has been applied to various contexts, including advanced manufacturing technology and sustainability in sport and recreation organizations (Pandza, Polajnar, & Buchmeister, 2005; Pfahl, 2010). Overall, The RBV provides a valuable framework for comprehending how firms can effectively utilize their internal resources and capabilities to attain and sustain a competitive advantage, thereby achieving superior performance across a variety of strategic planning contexts.

However, in the context of big data, an extension of RBV into the KBV has been proposed to emphasize the strategic significance of knowledge as the most pertinent resource for value creation in contemporary firms (Maijanen, 2020). This extension posits that the fundamental component of resources ought to be knowledge, encompassing both tangible and intangible forms, and elucidates how firms should be structured to generate and capitalize on knowledge (Yin, Chen, & Zhao, 2019). furthermore, the KBV posits that knowledge is a firm's most important productive resource, leading to varying levels of firm performance (Fu, 2022).

In the context of big data, the KBV suggests that big data can serve as a catalyst for the deliberate exploration of market and resource innovation opportunities, providing corporations with a competitive advantage (Mani, Delgado, Hazen, & Patel, 2017). Additionally, the KBV suggests that knowledge should be the primary component of resources, and firms should be structured to create and utilize knowledge. This aligns with the concept that big data can be considered explicit knowledge within the KBV (Franke & Hiebl, 2022).

Moreover, the KBV is an extension of the RBV, considering knowledge-based assets as an emerging perspective for achieving competitive advantage, beyond conventional factors of production such as labor, capital, and land (Hameed, Arshed, & Munir, 2021). This extension underscores the strategic importance of knowledge as the most pertinent resource for value creation in contemporary firms (Maijanen, 2020).

## 2.3 Knowledge based view

In the realm of strategic planning, the KBV of the firm is pivotal. The KBV underscores that a firm's capabilities and competitive advantage are rooted in the adept management of knowledge within the organization (Grant, 2006). Knowledge management is increasingly acknowledged as a fundamental component in strategic planning, with the proficient utilization of organizational knowledge being imperative for managerial decision-making and strategic triumph (Aliaga, 2000). Despite this acknowledgment, there remains a gap in comprehending the knowledge-based precursors of strategic planning capabilities, underscoring the necessity for additional research in this domain (Hughes & Hodgkinson, 2021).

Strategic planning, when guided by knowledge management practices, has the potential to enhance organizational performance. The amalgamation of knowledge among business and IT executives, as elucidated by the KBV, can bolster strategic alignment processes and contribute to organizational prosperity (Padukkage, 2016). Moreover, strategic planning is intricately connected to strategic leadership, strategic thinking, and organizational performance, underscoring the significance of these facets in propelling strategic success (Hunitie, 2018).

Moreover, the utilization and amalgamation of internal and external knowledge are pivotal determinants of a firm's innovative performance, as proposed by the KBV (Tang Wang & Libaers, 2016). Strategic planning is also correlated with enhanced corporate performance, as demonstrated in studies focusing on small business firms in diverse contexts, including Middle Eastern countries (Aldehayyat & Twaissi, 2011).

The KBV in the context of digitalization This extension highlights the strategic significance of knowledge as the most pertinent resource for value creation in modern firms. It acknowledges the substantial expenses associated with consensus decision-making due to the challenges in conveying tacit knowledge, highlighting the importance of leveraging knowledge in decision-making processes. Furthermore, the KBV explores whether digitalization enables firms to realize ambidextrous innovation, indicating the potential for digitalization to impact innovation processes within firms. Within the realm of digital mergers and acquisitions, the KBV perspective is concerned with the acquisition of knowledge for the purpose of replication, particularly in digital industries, where digital mergers and acquisitions can rapidly furnish complements to the acquirer's existing digital knowledge base. Additionally, in the context of digital venture ideas, entrepreneurial capabilities and prior knowledge play a significant role in generating new digital venture ideas, underscoring the importance of knowledge in the digital context. Moreover, the KBV has gained prominence in understanding how knowledge affects radical innovation, emphasizing the role of the knowledge base, market knowledge acquisition, and internal knowledge sharing in driving radical innovation in the digital era (Zhou & Li, 2012).

These references collectively support the understanding of the KBV in the context of digitalization, highlighting the strategic significance of knowledge as a critical resource for firms navigating the digital landscape.

The KBV emphasizes the high costs of consensus decision making due to the challenges of communicating tacit knowledge (Grant, 1996). On the other hand, the data-driven approach is gaining prominence due to its provision of insights for decision-making and easy implementation (Sadeghi, Amiri, & Mooseloo, 2021). In a data-driven culture, decisions are predicated upon empirical, verifiable data, with a foundational reliance on data-driven trend identification and future need projections (Joshi, Gertner, Roberts, & El-Mohandes, 2021).This is in line with the practice of basing decisions on the analysis of data rather than purely on intuition, as emphasized in the context of DDDM (Provost & Fawcett, 2013). Furthermore, the DDDM process involves using data-related evidence and insights to guide the decision-making process and verify the plan of action before it is committed (Yu et al., 2021).

The knowledge-based perspective of the firm has profound implications for the sources of competitive advantage, the architecture of decision-making processes, and the demarcation of organizational boundaries (Gehani, 2002). This is complemented by the idea that the main challenge in DDDM is not the acquisition of raw data itself, but the challenge of extracting useful knowledge from it (Ebel, Gülle, Lingenfelder, & Vogelsang, 2022). Moreover, the practice of DDDM is highlighted as a gold standard in science, industry, and public policy (Lin, Lisnic, Akbaba, Meyer, & Lex, 2023). It is also noted that DDDM uses data-driven prediction and knowledge-based detection to inform decision-making processes (Marschollek et al., 2019).

## 2.4 Dynamic capability view

Digital transformation stands apart from traditional strategic change (Warner & Wäger, 2019). Standard capabilities are now easily outsourced due to their ease of replication (D. J. Teece, 2014) therefor DCs are pivotal for digital transformation. They govern the frequency of change in an organization's standard capabilities (D. J. Teece, 2007), not easy to replicate (D. J. Teece, 2014), and permit organization to modify its business model (Helfat & Winter, 2011).

All conditions would be met if the necessary DC are developed in-house rather than purchased (D. Teece & Leih, 2016). Because, digital transformation involves altering the organizational business model, which involves re-evaluating how value is created and delivered, and how profits are captured, by overseeing a set of interconnected activities (Zott, Amit, & Massa, 2011) and every business model is more specific to its context (industry) than it is to technology (D. J. Teece, 2018).

DCs refer to the ability to detect potential threats and opportunities, capitalize on opportunities, and adapt to changes in the environment (Teece, 20078) i.e.

digital transformation in the context of this study. (Warner & Wäger, 2019). Warner and Wäger (2019) delineate three sub-capabilities of digital transformation capability: navigating the innovation system, redesigning internal structures, and enhancing digital maturity as shown in fig 1. Implementing big data in organizations through organizational capabilities such as DSP, DDC, and TMC hinges on the sub-capability of digital transformation known as redesigning internal structures. This is crucial for realizing the full potential of strategic change (Bharadwaj et al., 2013; Karimi & Walter, 2016; D. J. Teece & Linden, 2017). Relationship among DCs, strategy and business model is well established (Achtenhagen, Melin, & Naldi, 2013; DaSilva & Trkman, 2014; D. J. Teece, 2018; Velu, 2017). Casadesus-Masanell and Ricart (2010) argued that it is strategy, which reflects organizational business model, and when an organization is undergoing digital transformation of its business model, that is one of the three capabilities within the sub-capability of redesigning internal structure, it should poses a digital strategy. Whereas, DaSilva and Trkman (2014) argued that strategy revolves around constructing DC to effectively address both current and future radical and dramatic situations. It is evident from the arguments that strategy should be tailored to fit the firm's business model. Companies undergoing digital transformation should be guided through DSP. Doz and Kosonen (2010) proposed a variety of actions, such as increasing the sensitivity of strategic planning and enhancing resource fluidity, to embed strategic agility into the renewal and transformation of a firm's business model, thereby accelerating the process.

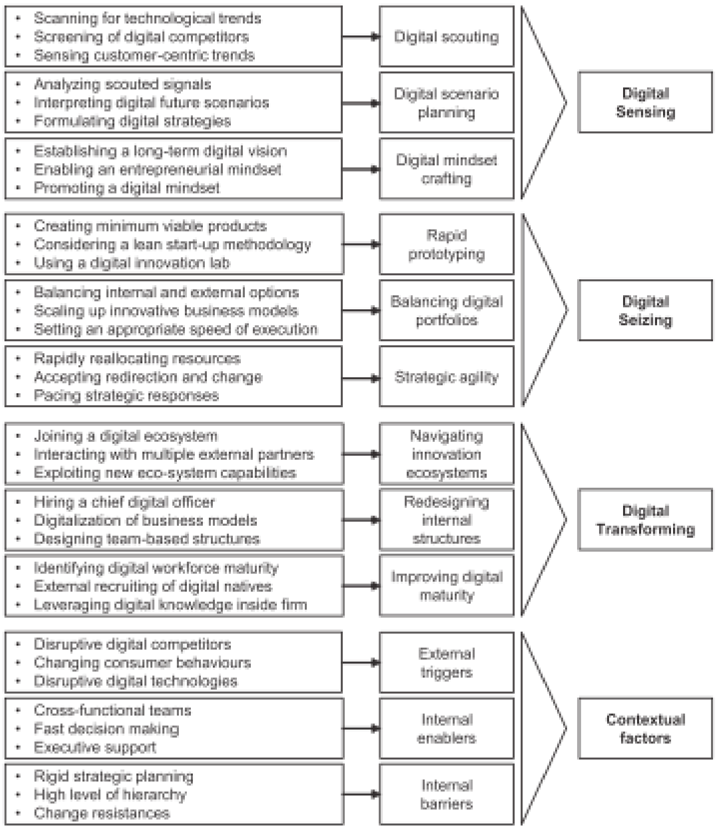


*Fig 1. Dynamic capacities model. Source: (Warner & Wäger, 2019)*

Navigating innovation ecosystems which is one of the sub-capability of digital transforming capability focused on digital ecosystem (Warner & Wäger, 2019). This ecosystem is constantly evolving and mainly depends upon mature IIOT in current study context. Current study suggests the transformation of business model, which means a transition from traditional way of value creation to digitalize way of value creation through BDAC's and it is mainly depends upon mature IOT (Warner & Wäger, 2019). Warner and Wäger (2019) has identified a number of organizations who has reshaped their business model using IOT platform and they also suggested the DL for any digital transformation based on dynamic capability theory.

Improving digital maturity of employee is among the sub-capability of digital transforming capability under dynamic capability theory (Warner & Wäger, 2019). Current study suggest that by incorporating DSC in organizational culture, DL can enhance the digital maturity of the employees so that they get gathered information from the multiple sources regarding industry for applying that information into their BDAC's for more sophisticated decision making.

Leadership lacking digital experience is seen as a major obstacle to the digital transformation of business processes (El Sawy, Kræmmergaard, Amsinck,

& Vinther, 2016). DL possesses the experience and skillset necessary for digital transformation (Weill & Woerner, 2018). Engagement of a chief digital officer is also an element of sub-capability redesigning internal structure for digital transforming capabilities (Warner and Wäger, 2019). DL improves all factors, including DSP, which reflects the firm's commitment to DDDM, DDC, and TMC, as the last factor of the sub-capability of redesigning internal structure is designing a team-based structure. The present study focuses on digital transformation capability, which involves the shift from a traditional business model to a digital one. This is achieved through the sub-capability of redesigning internal structure, led by a digitally experienced leader (DL). This leader formulates a DSP for DDDM by implementing big data solutions. Additionally, they design a team-based structure through DDC and TMC.

## 2.5 Digital leadership

As a DL, it is crucial to stay informed and up-to-date with the latest trends, technologies, and strategies in the digital landscape. To effectively lead in the digital realm, one must possess a deep understanding of digital transformation, data analytics, cybersecurity, artificial intelligence, and other relevant areas.

Digital transformation refers to the systematic integration of digital technologies across all facets of a business, thereby fundamentally altering its operational dynamics and enhancing the delivery of value to customers. Digital transformation entails utilizing technologies like cloud computing, the IoT, and automation to optimize processes, elevate customer experiences, and foster innovation.

Data analytics is a crucial component of DL, as it enables organizations to derive valuable insights from vast and complex datasets. By utilizing tools like predictive analytics, machine learning, and data visualization, DL can make data-driven decisions, enhance operations, and identify new business opportunities.

Cybersecurity is another critical aspect of DL, especially in the contemporary interconnected environment, where cyber threats are evolving to be more sophisticated. DL must prioritize cybersecurity measures to protect their organization's data, systems, and reputation from cyber attacks.

Artificial intelligence is transforming numerous industries by empowering machines to execute tasks that traditionally necessitate human intelligence, including natural language processing, image recognition, and decision-making. DL need to understand how AI can be leveraged to improve business processes, personalize customer experiences, and drive innovation.

In addition to these key areas, DL should also be familiar with topics such as digital marketing, e-commerce, social media management, and agile methodologies. By staying informed and continuously learning about the latest digital trends and technologies, DL can effectively navigate the digital landscape and drive their organizations towards success in the digital age.

## 2.6 Big data analytical capabilities

To enhance BDAC's as a DL, it is essential to understand the interplay between DL, organizational culture, and technological competencies. Tiandong Wang, Lin, and Sheng (2022) highlight that DL positively influences exploratory innovation, with digital entrepreneurial orientation and organizational culture mediating this relationship. Moreover, the mediating effect is further enhanced by BDAC's, emphasizing the importance of leveraging data analytics to drive innovation.

Abbu and Gopalakrishna (2022) emphasize the critical role of BDAC's in digital transformation, particularly in acquiring and analyzing large datasets for decision-making. This underscores the significance of utilizing big data to harness the full potential of digital technologies within organizations.

Schmidt, van Dierendonck, and Weber (2023) provide a framework for BDA leadership competencies, emphasizing the importance of data analytical skills, self-efficacy, problem-spotting abilities, and visionary leadership in driving successful data-driven initiatives. This framework can guide DL in developing the necessary skills to effectively utilize BDA within their organizations.

Furthermore, (Hao, Zhang, & Song, 2019) discuss how BDAC's moderates the impact of big data on various performance metrics, highlighting the importance of developing strong analytical capabilities to maximize the benefits of big data initiatives. By fostering a culture of DDDM and investing in the right talent, organizations can build sustainable BDAC's.

As a DL looking to enhance BDAC's, it is crucial to focus on developing leadership competencies, fostering a data-driven culture, and investing in the necessary skills and technologies to leverage big data effectively. By understanding the mediating role of DL, organizational culture, and data analytics capabilities, DL can drive innovation, improve decision-making, and gain a competitive edge in the digital landscape.

## 2.7 Data driven decision-making

In the realm of big data in industrial settings, data-based decision-making plays a crucial role in utilizing the vast amounts of data available to drive informed decision-making processes. Provost and Fawcett (2013) highlight the substantial improvement in business performance achievable through DDDM, big data technologies, and data science techniques, emphasizing the importance of leveraging big data to enhance decision-making processes in industrial contexts.

Additionally, Janssen, van der Voort, and Wahyudi (2017) discuss the factors that influence the quality of decision-making in the context of big data. Understanding these factors is essential to ensure that decisions made based on big data are of high quality and result in positive outcomes in industrial settings. Elgendy and Elragal (2016) emphasize the role of BDA in supporting the decision-making process, stressing the significance of using data analytics tools to extract valuable insights for decision-making in industrial environments.

Moreover, Siniak (2020) specifically focus on the integration of big data into decision-making within the real estate industry, demonstrating how various sectors are adapting to the era of big data to enhance their decision-making processes. This sector-specific insight showcases the applicability and benefits of incorporating big data into decision-making across diverse industrial domains.

The integration of big data into decision-making processes in industrial contexts presents significant opportunities for organizations to make data-driven decisions that can lead to improved performance, efficiency, and competitiveness. By leveraging BDA and DDDM approaches, industries can harness the power of data to drive innovation and strategic decision-making.

## 2.8 Digital strategic planning

DSP for BDAC’s is crucial for organizations looking to effectively leverage big data. Research by Akter et al. (2016) emphasizes the importance of aligning business strategy with BDAC’s to enhance firm performance (Akter et al., 2016). This alignment is essential for sustainable supply chain agility, as highlighted by Dubey, Gunasekaran, Childe, Papadopoulos, et al. (2019), who define BDAC’s as a set of tools and processes enabling organizations to process and analyze data for DDDM.

Furthermore, the study by Bhatti et al. (2021) underscores the significance of BDA in enhancing strategic performance, especially in the digital era Bhatti et al. (2021) and Mikalef et al. (2018) introduces the concept of big BDAC’s as a proficiency in leveraging big data for strategic and operational insights, essential for transitioning to a data-driven era (Tang Wang & Libaers, 2016).

Incorporating BDAC’s into strategic planning requires continuous updates to digital infrastructure, experimentation with advanced analytical technology, recruitment of skilled personnel, and integration of analytics insights into decision-making processes, as suggested by (Tiandong Wang et al., 2022). This aligns with the findings of (X. Su et al., 2022), which highlight BDAC’s as crucial resources for improving organizational performance through dual innovations (X. Su et al., 2022).

## 2.9 Digital department collaboration

DDC refers to the use of digital tools and technologies to facilitate communication, cooperation, and coordination among different departments within an organization. This approach aims to enhance efficiency, productivity, and innovation by breaking down silos and promoting cross-functional collaboration.

One key reference that provides insights into DDC is the research article by Bughin et al. (2018) titled "Collaborating at scale: How can digital technology help?" This study explores the impact of digital technologies on collaboration within and across organizations. The authors highlight the role of digital platforms, such as project management tools, communication apps, and collaborative software, in enabling seamless collaboration among departments. They emphasize the importance of aligning digital tools with organizational goals and fostering a culture of collaboration to maximize the benefits of DDC.

Another relevant reference is the book by Brynjolfsson and McAfee (2014) titled "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies." In this book, the authors discuss the transformative power of digital technologies in reshaping how organizations operate and collaborate. They argue that digital tools have the potential to revolutionize departmental collaboration by enabling real-time communication, data sharing, and decision-making across different functions. The book provides examples of companies that have successfully leveraged DDC to drive innovation and competitive advantage.

Furthermore, the research paper by Leonardi and Meyer (2015) titled "Social media as social lubricant: How ambient awareness eases knowledge transfer" offers valuable insights into the role of social media in facilitating departmental collaboration. The authors examine how platforms like Twitter, Facebook, and LinkedIn can create ambient awareness among employees, leading to improved knowledge sharing and collaboration. They suggest that organizations can harness social media tools to bridge communication gaps between departments and foster a culture of collaboration and knowledge exchange.

DDC is a critical aspect of modern organizational dynamics, and leveraging digital tools and technologies can significantly enhance inter-departmental communication and cooperation. By drawing on insights from research articles, books, and studies like those mentioned above, organizations can develop effective strategies for promoting collaboration across departments and driving innovation and success in today's digital age.

## 2.10 Top management commitment

TMC is a crucial factor that influences various aspects of organizational performance and success. Research by Colwell and Joshi (2013) highlights that TMC moderates the relationship between institutional pressures and corporate environmental responsiveness, ultimately impacting organizational performance. Similarly, Yusliza et al. (2019) emphasize the importance of TMC in realizing the organization's mission and improving firm performance.

Furthermore, studies by Tarigan, Siagian, and Jie (2020) and Tanuwijaya, Tarigan, and Siagian (2021) demonstrate the significant role of TMC in influencing purchasing strategy, green purchasing, and supplier relationship management, which in turn affect firm performance. Burki, Ersoy, and Najam (2019) suggest that comprehensive commitment by top management is essential for implementing green innovations and achieving customer cooperation.

Moreover, Michaelis, Stegmaier, and Sonntag (2009) discuss how affective commitment to change, charismatic leadership, and trust in top management positively impact innovation implementation behavior. Additionally, Amir, Rehman, and Khan (2020) highlight the importance of TMC in environmental management accounting and control systems for enhancing environmental performance and gaining a competitive advantage.

TMC plays a pivotal role in driving organizational change, innovation, sustainability, and performance. It influences various aspects such as environmental responsiveness, purchasing strategies, innovation implementation, and customer cooperation, ultimately contributing to the overall success of the organization.

## 2.11 Digital social capital

DSC is a crucial element in the contemporary era, particularly in the context of digital transformation and the utilization of digital technologies. Research has shown that digital capital, encompassing competences and technologies related to the digital realm, is distinct from traditional forms of capital such as cultural, social, and economic capital (Leguina & Downey, 2021). By engaging in digital activities within platforms like Alibaba, entrepreneurs can enhance their social capital within digital ecosystems, leading to improved access to knowledge and resources (L. Li, Su, Zhang, & Mao, 2018). Moreover, the accumulation of digital capital enables individuals to strengthen and maintain broad social networks, which aligns with various social theories (Lybeck et al., 2023).

The concept of DSC extends beyond individual interactions to impact broader societal aspects. Social capital has been found to facilitate increased digital access, which is crucial for effectively leveraging digital technologies (Teng Wang, Guo, & Wu, 2021). Additionally, the mediating role of social capital in the digital transformation of startups has been emphasized, highlighting the significance of connections and networks in driving digital innovation (Nguyen, Ghi, & Nguyen, 2023). Furthermore, the use of digital technologies has been acknowledged as a means to enhance social capital, particularly in areas such as healthcare services and public engagement (Jaewon Lee & Kim, 2021; Mandarano, Meenar, & Steins, 2010).

In the realm of digital capitalism, the importance of digital labor and the shift towards a "social factory" dominated by digital technologies have been underscored, indicating the pervasive influence of digital capital in contemporary economic structures (Wu, 2021). Additionally, the relationship between digital capital and other forms of capital, such as economic, cultural, and political capital, underscores the interconnectedness of various societal resources and the role of digital technologies in transforming these dynamics (Rahmawati, Faubiany, Siregar, & Sukarno, 2021).

The synthesis of these studies highlights the multifaceted nature of DSC, its implications for individual and collective interactions, and its role in shaping contemporary social, economic, and political landscapes. Embracing digital technologies and leveraging DSC are essential components for navigating the complexities of the digital age and driving innovation and societal development.

## 2.12 Digital literacy

DLIT in the context of big data is a crucial skill set that individuals need to effectively navigate and utilize vast amounts of data in today's digital age. Understanding DLIT in the realm of big data involves not only the ability to find, evaluate, and share information using digital tools but also to comprehend and analyze complex datasets to derive meaningful insights.

Studies have highlighted the importance of DLIT competencies for learners in open and distance education (Ozdamar-Keskin, Ozata, Banar, & Royle, 2015). These competencies encompass various aspects such as computer literacy, technology literacy, information literacy, media literacy, visual literacy, and communication literacy. Moreover, the development of DLIT is crucial in the increasingly digital society (Tejedor, Cervi, Pérez-Escoda, & Jumbo, 2020). Training in competencies within the scope of DLIT is essential, especially in the context of a rapidly evolving digital landscape.

DLIT in the big data context also intersects with information literacy and media literacy (Koltay & society, 2011). These literacies focus on critical approaches towards media messages and the evaluation of information sources, which are essential skills when dealing with large datasets and diverse sources of information in big data environments. Furthermore, the ability to process data and understand the objectives of digital displays is a key component of DLIT (Pratolo & Solikhati, 2021), which becomes even more pertinent when dealing with the vast amounts of data present in big data scenarios.

In the era of big data, the improvement of data literacy is crucial for effective learning (F. Liu, Liu, Wang, & Zhang, 2023). Strategies for enhancing data literacy in the context of big data are essential for leveraging data-driven insights to enhance desired outcomes.

DLIT in the context of big data is a multifaceted skill set that encompasses competencies in finding, evaluating, and utilizing information in digital environments, particularly when dealing with large datasets. Developing DLIT skills in the realm of big data is essential for individuals to make informed decisions, derive insights, and effectively engage with data-driven technologies in various professional and educational settings.

## 2.13 Industrial internet of things

The IIoT is a transformative technology that aims to enhance industrial processes and systems by leveraging smart sensors, fast communication protocols, and robust cybersecurity measures (Latif et al., 2021; Zhu, Wang, & Zhang, 2020). IIoT incorporates concepts from the IoT to revolutionize traditional industrial practices and enable advanced automation (Huma et al., 2021). One of the key advantages of IIoT is its potential to interconnect industries, leading to significant business opportunities and economic growth (Vaiyapuri, Sbai, Alaskar, & Alaseem, 2021). This technology offers ubiquitous connectivity, advanced data analytics capabilities, and enhanced decision support systems, fostering innovation and competitiveness across industrial domains (Kumar & Tripathi, 2021). Furthermore, IIoT facilitates the digitization and integration of industrial assets, improving productivity and economic impact in the manufacturing sector (Alabadi, Habbal, & Wei, 2022). Despite its benefits, the complexity of IIoT architecture poses security and privacy challenges (Fun & Samsudin, 2021). The proliferation of IIoT technologies has attracted malicious actors to launch cyberattacks, highlighting the need for robust intrusion detection mechanisms (Abdel-Basset et al., 2021). Ensuring the scalability, robustness, and security of IIoT systems remains a pressing concern for industrial applications (Moens et al., 2020). In conclusion, the IIoT represents a paradigm shift in industrial operations, offering opportunities for efficiency enhancement and innovation. Addressing security vulnerabilities, ensuring privacy, and overcoming scalability challenges are crucial for the successful implementation and widespread adoption of IIoT in industrial settings.

## 2.14 Digital leadership and big data analytical capabilities

In the digital age, a leader must possess a transformative vision, DLIT as well as general leadership abilities such as team building and collaboration. (Kane, Phillips, Copulsky, & Andrus, 2019). Leaders should take the initiative to foster collaboration among employees and facilitate forward-thinking by leveraging information technology (Anak Agung Sagung & Sri Darma, 2020). Anak Agung Sagung and Sri Darma (2020) and Kane et al. (2019) claimed that these characteristic belongs to DL. The implementation and progress of BDAC's are closely linked with decision-making culture and IT leadership. (Grover et al., 2018). "BDAC is defined as the ability of the firm to capture and analyse data toward the generation of insights, by effectively deploying its data, technology, and talent through firm-wide processes, roles and structures" (Gupta & George, 2016; Kiron, Prentice, & Ferguson, 2014; Wamba et al., 2017). Kane et al. (2019) asserts that technology comprehension is the top three skills that DL should hold. This indicates that IT leadership is considered one of the characteristics of a DL. BDACs, rooted in decision-making culture and led by a DL, are expensive and difficult to replicate (Grover et al., 2018). The authors previously noted that 70% of transformations fail, McAfee et al. (2012) emphasizing that a lack of appropriate leadership is a primary contributing factor. Leadership that possesses a clear BDA strategy is more likely to achieve success (Grover et al., 2018). In a case study by Dremel, Wulf, Herterich, Waizmann, and Brenner (2017), the example of a car manufacturing company, AUDI AG, is discussed. A chief digital officer led the transformation of this company. whereas Janssen et al. (2017) discusses the case of implementing BDA in a Dutch tax organization, a process that was spearheaded by directors. Both the chief digital officer and the directors share the characteristic of being DL. Grover et al. (2018) contend that IT leadership, which falls under the umbrella of DL (Kane et al., 2019), is presented with outstanding opportunities to invest in BDA. The dynamic capability perspective also suggests that organizations can create or reconfigure their existing capabilities or competencies to effectively address environmental threats (D. J. Teece, Pisano, & Shuen, 1997) and it is already discussed that DL step forward to frontward routing by utilizing information technology (Anak Agung Sagung & Sri Darma, 2020). Furthermore hiring a DL is also suggested by Warner and Wäger (2019) who pointed out the importance of the DL hiring under the sub-capability redesigning the internal structure.  Based on these arguments current study proposed below hypothesis.

$H_1$: Digital leadership (DL) has a positive effect on big data analytical capabilities (BDAC).

## 2.15 Digital leadership and digital strategic planning

DL involves leveraging resources to enhance or add value to our activities, reflecting the strategic mind-set of the leader (Anak Agung Sagung & Sri Darma, 2020). The strategic mind-set embodies the strategic planning that the leader envisions for the organization, detailing where we are currently and where we aim to be in the future. Kane et al. (2019) DL possesses a digitalized and transformative vision, enabling the implementation of digital technologies like big data for DDDM through a DSP. Understanding digital future scenarios and devising a digital strategy is also aided by the DC perspective, particularly through its sub-capability of digital scenario planning (Warner & Wäger, 2019).

Persson (2020) also claimed that a clear vision is crucial for developing a robust strategic plan and DL possess a digitalized vision to create a DSP that enhances BDAC’s. Base on these discussion current study define DL as “a portfolio of digital, business and strategic leadership skills (interpersonal and intrapersonal skills to create value through driving action, strategic mind-set and decision making)” (Benitez, Arenas, Castillo, & Esteves, 2022). DL are also regarded as crucial for the implementation of digital technologies such as BDA and DDDM by integrating information technology with the business strategy of the firm. (Benitez et al., 2022). Based on these arguments current study proposed below hypothesis.

$H_2$: Digital leadership (DL) has a positive impact on digital strategic planning (DSP).

## 2.16 Digital leadership, digital strategic planning and big data analytical capabilities

Strategy may influence capabilities (Benitez et al., 2022). The capability of BDA and the strategic business plan can be aligned together. (Akter et al., 2016). The alignment of strategic planning and BDAC’s is contingent upon having a visionary leader. (Akter et al., 2016) because A vision serves as the foundation for strategic planning (Persson, 2020) In the current study scenario, the leader possesses a digital vision, which forms the basis for the DSP. A digital-centric strategic planning approach, rooted in a digitalized vision, will have a positive impact on BDAC’s. This is because the DSP of the firm will be designed in alignment with the BDAC’s. McAfee et al. (2012) also emphasized that the success of companies does not hinge on the size of the data or its quality, but rather on having clear goals. This is because the power of big data cannot replace the necessity for vision. They also emphasize the importance of aligning or synchronizing strategies with BDAC’s. The more synchronized the BDAC’s are with the business strategies, the greater the synergy among different functional units, leading to a positive impact on desired outcomes. (BDA capabilities) (McAfee et al., 2012).

The discourse on the interplay between BDAC’s and DL as well as DSP has been comprehensively discusses in the preceding discussion. There is limited literature that delves into the mediating role of DSP in the relationship between DL and DSP. The digital sensing capability, particularly through its sub-capability of Digital Scenario Planning, empowers DL to craft a DSP.

Additionally, another sub-capability of Digital Sensing, referred to as Digital Mind Crafting, enables DL to foster a digital mindset within the organization (Warner & Wäger, 2019) by matching its DSP and BDA capabilities (McAfee et al., 2012). The dynamic capability perspective, particularly through its sub-capability of redesigning internal structure, supports the notion that organizations should hire a DL for the implementation of digital technologies such as Big Data for DDDM (Warner & Wäger, 2019). As previously elaborated, the DSP process is anticipated to exert a discernible impact on the development and enhancement of BDAC's. Benitez et al. (2022) posit that strategic initiatives possess the potential to significantly shape and enhance organizational capabilities, particularly when these strategies are meticulously aligned with the organizational capabilities (Akter et al., 2016). DL, through their transformative vision and IT leadership skills (Kane et al., 2019), will establish alignment between Digital Strategy Planning (DSP) and Big Data Analytics (BDA) capabilities. This alignment will enable DSP to effectively influence BDA capabilities. Based on these arguments current study proposed below hypothesis.

$H_3$: Digital strategic planning (DSP) mediates the relationship among digital leadership (DL) and big data analytical capabilities (BDAC's).

## 2.17 Digital leadership and digital departmental collaboration

The current study is grounded in the sub-capability of redesigning internal structure, which is a critical aspect of the broader digital transformation capability. A team-based structure is one of the elements of redesigning the internal structure that supports DDC. Oberer and Erkollar (2018) Oberer and Erkollar (2018) advocate that in the progressive phase of Industry 4.0, characterized by the adoption of novel technologies, the cultivation of cooperation and collaboration is essential, facilitated through digital platforms like cloud computing. The pivotal role of DLs is crucial in the development of DDC through its collaborative attributes (Kane et al., 2019). DDC means working relation between departments within a company through digital platform to enhance BDA capabilities for quality DDDM. Janowski, Estevez, and Baguma (2018) Shariq conducted a case study and identified several factors that impact departmental collaboration, such as facilitating a platform for stakeholders to collaborate and integrating new technologies to enhance departmental collaboration. In the present study, these two factors are collectively analyzed under the framework of Departmental Digital Collaboration (DDC). Legner et al. (2017) posited that the organizational IT functions ought to undergo a transformative process, characterized by the adoption of new internal organizational structures, alongside novel modes of collaboration and alignment with business departments. The digitalization process is facilitated by the convergence of several IT megatrends, including big data, cloud computing, mobile technology, social media, and smart technologies. To successfully digitalize their operations, organizations must undergo a socio-technical transformation that impacts their business processes (Legner et al., 2017). The rising demand for digital technologies, such as cloud computing, places significant pressure on organizational leaders to adapt and integrate these technologies effectively (Legner et al., 2017). Warner and Wäger (2019) argue that in any given industry, the introduction of a platform is typically spearheaded by the leading organization within that industry. The same phenomenon can also be observed within organizations. If a digital platform is being considered, an organizational leader, who in the context of the current study is referred to as the DL, would typically lead the orchestration of that platform. Wasono and Furinto (2018) claim that DL is essentially a fusion of leadership skills and digital capabilities, aimed at optimizing the outcomes of digital technologies. DL is essentially a fusion of leadership skills and digital capabilities, aimed at optimizing the outcomes of digital technologies. DL's innovative vision, networking intelligence, adaptability, and digital intelligence make it a crucial leadership style for fostering fluidity in departmental collaboration. Through innovative vision, DL can envision new ways of collaboration, while networking intelligence enables them to connect with relevant stakeholders. Their adaptability allows them to navigate changing circumstances, and their digital intelligence ensures they leverage technology effectively in collaboration efforts (Klein, 2020). Dynamic capability theory also advocates for the importance of DL in digital transformation. One of its sub-capabilities, the redesigning of the internal structure of an organization, is founded on the premise of hiring a DL (Warner & Wäger, 2019). Based on the argument current study proposed below hypothesis.

$H_4$: Digital leadership (DL) has a positive effect on digital departmental collaboration (DDC).

## 2.18 Digital leadership, digital departmental collaboration and big data analytical capabilities

The integration of digital technologies has facilitated the emergence of expansive and intricate concepts, including big data, cloud computing, and IoT. These technologies have revolutionized data collection, enabling the exchange and real-time processing of a broad spectrum of valuable data (Tijan et al., 2021). Collaboration among different departments is often cited as a key factor for success in business processes (Tijan et al., 2021) BDAC's necessitate departmental collaboration to establish a seamless flow of activities (Janssen et al., 2017). Enhancing fluidity in departmental collaboration can significantly improve the effectiveness of BDAC. inherently possesses greater fluidity compared to traditional collaboration methods (Warner & Wäger, 2019) due to the seamless integration of multiple information sources facilitated by digital technologies (Tijan et al., 2021). The significance of digital cross-departmental initiatives, such as Big Data Analytics (BDA), has also been emphasized (Dremel et al., 2017). BDAC's improvement can be facilitated by embedding new digital technologies into aligned business processes and integrating multiple information platforms or systems and data sources through DDC (Tijan et al., 2021). In their discussion on the digital transformation capabilities of the dynamic capability view, (Warner & Wäger, 2019) argue that the digital transformation of business processes hinges on changes in both business processes and collaboration approaches. However, they also suggest that to effect changes in business processes, broader changes are necessary in collaboration approaches.

Utilizing digital technology in accordance with organizational goals is a key success factor in the digitalization process, particularly in the implementation of big data initiatives, a responsibility typically entrusted to the DL (Tijan et al., 2021). DL's adaptive characteristic, as discussed by Klein (2020), enables them to adjust to digital technologies effectively, leveraging their digital intelligence. Additionally, their networking intelligence, also highlighted by Klein (2020), empowers them to orchestrate DDC, ensuring the achievement of desired outcomes, particularly the quality of DDDM through BDAC's. Janssen et al. (2017) assert that departmental collaboration is a pivotal component for the successful implementation of BDACs. However, Warner and Wäger (2019) argue that DDC introduces a unique fluidity into the departmental collaboration process, which in turn positively influences the efficacy of BDACs. In summary, the authors suggest that the relationship between the DL and BDACs is influenced by DDC. Warner and Wäger (2019) additionally propose that the digital transformation capability, as viewed through the dynamic capability lens, is contingent upon the deployment of a DL and the effective exploitation of new ecosystem capabilities. On the other hand, the deployment of DDC by the DL represents the exploitation of new ecosystem capabilities, aimed at enhancing the quality of decision-making through BDA. Based on these hypothesis current study proposed below hypothesis-

$H_5$: Digital departmental collaboration (DDC) mediates the relationship between digital leadership (DL) and big data analytical capabilities (BDAC's).

## 2.19 Digital leadership and top management commitment

There has been much research conducted on the impact of TMC on firm-level efforts (Dubey, Gunasekaran, & Ali, 2015; Dubey et al., 2016; Graves, Sarkis, & Gold, 2019). "TMC is the extent to which top manager demonstrate commitment to drive the firm's strategy" (Graves et al., 2019). Top managers are inclined to communicate the significance of desired outcomes, such as BDACs, by elucidating their importance, delineating the company's strategy, and establishing objectives (Colwell & Joshi, 2013). Organizations' strategic management endeavors have been hindered by insufficient support from top management (Rodgers, Hunter, & Rogers, 1993). Leadership involves establishing policies and objectives for capability development that align with the long-term vision of the organization (Dubey et al., 2015). Warner and Wäger (2019) proposed that the DL serves as a key component within the sub-capability of redesigning the internal structure, which is integral to the digital transformation capability as viewed through the dynamic capability perspective. Through the influential characteristic of the DL, as emphasized by Kane et al. (2019), it is imperative that one of the primary goals of the DL is the development of TMC. This capability is crucial for achieving objectives such as BDA and DDDM. Klein (2020) documented that throughout the digital transformation process, the DL should assume the role of a motivational coach for the senior managers within the organization. A motivating coach role for the DL entails encouraging the top management of the firm to overcome their apprehensions about change and cultivate a culture that is conducive to digital transformation (Klein, 2020). Achieving objectives, such as implementing big data solutions, without compromising profit margins can be accomplished through the TMC. DL must ensure that organizational goals are aligned with the objective of achieving DDDM through BDAC's (Dubey et al., 2015). one of the goals of the DL should be to develop TOP (Kane et al., 2019). Based on these argument and theoretical background, current study proposes below hypothesis-

$H_6$: Digital leadership (DL) has a positive effect on Top management commitment (TMC).

## 2.20 Digital leadership, top management commitment and big data analytical capabilities

The successful full implementation of planned goals is more likely when an organization has strong TMC (Rodgers et al., 1993). "TMC is the extent to which top manager demonstrate commitment to drive the firm's strategy" (Graves et al., 2019). El-Kassar and Singh (2019) further propose that the presence of TMC and access to large-scale data are imperative for effectively managing technological challenges. The implementation of technologies like big data is heavily impacted by the knowledge and beliefs held by top management (El-Kassar & Singh, 2019). Gunasekaran et al. (2017) Gunasekaran et al. (2017) conducted a study focusing on top management in the context of big data and found a positive correlation between TMC and the successful implementation of big data and predictive analytics. The mediation hypothesis of TMC was also examined in the context of the relationship between connectivity and big data predictive analysis. The results of the study supported this hypothesis (Gunasekaran et al., 2017). Even with the right drivers in place, achieving desired outcomes may be challenging without TMC, as TMC is crucial for overcoming technological obstacles (El-Kassar & Singh, 2019; Gunasekaran et al., 2017). The commitment of top management is vital for cultivating capabilities and aiding the company in reaching its objectives (Chadwick, Super, & Kwon, 2015; Sirmon, Hitt, & Ireland, 2007).

Within the dynamic capability view, the digital transformation capability encompasses a sub-capability known as redesigning the internal structure, which includes the component of appointing a chief digital officer (Warner & Wäger, 2019). The appointment of a chief digital officer can be considered as the deployment of a DL. The role of the DL in enhancing BDACs is thoroughly discuss above. The implementation and execution of a clearly delineated BDA strategy can significantly augment an organization's prospects for success (Grover et al., 2018). Even with foundational elements such as a DL in place, the TMC plays a crucial role in the successful implementation of a BDA strategy. This is due to the potential challenges that may arise during the execution phase, which could be difficult to overcome without the strategic guidance and oversight provided by the TMC (El-Kassar & Singh, 2019; Gunasekaran et al., 2017). The establishment of a TMC is a critical objective for a DL due to its influential nature. Top management, responsible for achieving objectives such as BDA and DDDM, can effectively leverage the TMC's strategic guidance and oversight to ensure the successful implementation of these initiatives (Kane et al., 2019). TMC is crucial for cultivating the capabilities (Chadwick et al., 2015; Sirmon et al., 2007) required to efficiently utilize data analytics and transition towards the adoption of DDDM practices across the organization. The DL is anticipated to fortify or elevate the TMC through its influential attributes. Simultaneously, the TMC is expected to exert a positive influence on the BDAC by virtue of its inherent ability to enhance capability. As stated, even with the necessary drivers in place, the desired outcomes may not be realized without top managerial commitment. This is because the TMC plays a crucial role in overcoming technological obstacles (El-Kassar & Singh, 2019; Gunasekaran et al., 2017). Based on these arguments current study proposed below hypothesis.

$H_7$: Top management commitment (TMC) mediates the relation between digital leadership (DL) and big data analytical capabilities (BDAC's).

## 2.21 Digital leadership and digital social capital

Value that come from the networks and relationships one has in a society or community is refer as social capital (ul zia, Burita, & Yang, 2022). The sharing of information and resources within a network of relationships is often seen as a key component of social capital (Y.-B. Wang & Ho, 2017). Relationships between individuals in an organization and outside parties can be crucial in facilitating knowledge creation and information sharing (Zhang & Peterson, 2011). These relationships can provide access to a diverse range of perspectives, which can be valuable in generating new ideas and insights through BDAC's. Social capital is categories under three dimensions structural social capital, relational social capital and cognitive social capital (Nahapiet & Ghoshal, 1998). Who will engage in order to foster relationships and how these relationships will be achieved is explained by structural social capital (Chow & Chan, 2008). Structural social capital is an organized pattern of relationships within a society or group. It includes the way roles, rules, and procedure are established and maintained, and how they shape the interactions and behavior of individuals within the society or group (ul zia et al., 2022; Uphoff & Wijayaratna, 2000). Structural social capital allows access to multiple parties for knowledge transmission and exchange, as well as increasing the chance to trade (Ansari, Munir, & Gregg, 2012).

Relational social capital refers to the social networks and connections that people have with each other, and the trust and norms that exist within those relationships through accepted norms, mutual trust, and connectedness with others (Cabrera & Cabrera, 2005). It represent the bonds that are form through these interactions and the trust and norms that exist within those relationships (Lefebvre, Sorenson, Henchion, & Gellynck, 2016). Relational social capital can be built through a variety of activities, such as participating in community groups, volunteering, or simply interacting with people on a regular basis. Expectations and obligations are the main two aspect of this dimension (Nahapiet & Ghoshal, 1998).

Cognitive social capital refers to the shared beliefs, values, and understanding that exist within an organization (Wasko & Faraj, 2005). Cognitive social capital is related with the shared systems of meaning, interpretations, and representations that exist among parties within an organization. It encompasses the collective knowledge, values, and beliefs of the organization's members, and how they understand and interpret the organization's purpose and mission (Nahapiet & Ghoshal, 1998). All the three component of social capital plays an important role in capability development (Ganguly, Talukdar, & Chatterjee, 2019). Current study author study social capital as DSC facilitated by DL through digital technologies. Current study defines DSC as the value created by relationships, trust, and networks established through technology and digital media. It is the accumulation of the benefits and resources, which comes from and to individuals and communities through their connections and activities on digital platforms.

While explaining the process of dynamic capability, Warner and Wäger (2019) describes that how digital transforming capability could be develop which has a sub-capability improving digital maturity. Therefore, improving digital maturity of employees is among one of the sub-capabilities of transforming capability under dynamic capability view that is possible through DL. Empowering and enabling employees to carry out new initiatives is another characteristic of DL (Kane et al., 2019). DL can make them empower and enabled for the effectiveness of BDAC's through arranging some get together within or outside the organization for acquiring some new and advance information and knowledge from the industry as per structural social capital (Chow & Chan, 2008) through digital technologies, which will be utilize for BDAC's. After a series of these network meetings employees will be able to develop their own personal relationship with the other employees within or outside of organization as relational social capital (Cabrera & Cabrera, 2005). Furthermore, with the passage of time these employees will be able to communicate through their own shared meaning and interpretation as categorized under cognitive social capital (Wasko & Faraj, 2005). All this process will be supported by DL because joining and exploiting the digital eco-system for acquiring information also depends DL (Warner & Wäger, 2019). Based on the arguments current study proposed below hypothesis.

$H_8$: digital leadership (DL) has a positive effect on digital social capital (DSC).

## 2.22 Digital leadership, digital social capital and big data analytical capabilities

Social capital accumulates the benefits and resources from individual and communities (ul zia et al., 2022). Similarly, when these data, information and knowledge would be collected through digital platform and the connection among parties are based on some digital platform and each party is comfortable in sharing the information through digital platform then the gained information through DSC will enhance BDAC. As Janssen et al. (2017) pointed out that the data is shared easily but sometimes information or knowledge associated with the data is not transferred so social capital is a good source for acquiring associated information and through digital technologies we have more fluid communication through DSC.

Digital technologies which can provide rapid response to technological and environmental changes like covid-19 pandemic required balance between internal and external collaboration through redesigning and manageable governance system (Warner & Wäger, 2019). External collaboration is hint toward social capital and DL, which would promote digital platform to build DSC among the employees of the firms within same industry (Eisenhardt & Martin, 2000; D. J. Teece et al., 1997). As it is digitally literate and understands technology and his prior experience will guide him that how to develop and promote digital platform for DSC (Kane et al., 2019). Bringing unconnected experience from the industry together through digital platform would bring convergence among them (Sebastian et al., 2017). Firms having transforming capabilities has agile, entrepreneurial mind set with external network building approach as well (Day & Schoemaker, 2016). This is how firms can respond to fast changing environments (Agarwal & Helfat, 2009; D. J. Teece, 2014).

Under dynamic capability, micro-foundation of transforming capability named navigating innovation ecosystems also support the argument that firms should create DSC by joining digital ecosystem, interacting with multiple external partners and by exploiting new ecosystems capabilities (Warner & Wäger, 2019). Once these DSCs become active in day-to-day firm's life, firms would be able to gain more information about the market, which they will utilize in their data analytics for reaching to some decisions and a variety and velocity of data will provide resilience the firm's decision making. Based on these arguments current study proposed below hypothesis.

$H_9$: Digital social capital (DSC) mediates the relationship between digital leadership (DL) and big data analytical capabilities (BDAC's).

## 2.23 Digital leadership and digital literacy

DL is the competence that consist of the abilities of employees to utilize digital technologies to perform their work (Cetindamar, Abedin, & Shirahada, 2021). Dynamic capability view also stresses a lot on the importance of DLIT, as Warner and Wäger (2019) claims digital maturity as one of the sub-capability of digital transforming capability.

The concept of DLIT in the context of big data is multifaceted and encompasses various skills and competencies essential for individuals to navigate the digital world effectively. DLIT is crucial for living, learning, and working in a digital society (Nabhan, 2021). It involves proficiency in ICT, information, data, media literacy, digital creation, problem-solving, innovation, communication, collaboration, participation, learning, development, identity, and wellbeing (Nabhan, 2021). Furthermore, DLIT is not just about technical skills but also about critical thinking and integration abilities in the digital economy (Chiu, Sun, & Ismailov, 2022). It is essential for individuals to have the ability to read and interpret data in the digital world and utilize digital tools effectively (Sangaji & Pribadi, 2023). In the context of big data, DLIT includes information literacy skills Gündüzalp (2021) and is fundamental for the future of education (Marisa & Djulia, 2022). The concept of DLIT has evolved to encompass various types of literacy, such as media literacy, information literacy, and DLIT (Novianti & Istiyanto, 2020). As the volume and complexity of data continue to grow, there is a need to develop big data literacy to support informed and reflective citizenship (Francois et al., 2020). This highlights the importance of understanding the potential and limitations of big data for statisticians and statistics consumers. Additionally, there is a call for greater efforts to educate people about big data and increase public literacy about big data practices (Sander & Policy, 2020). In the context of DLIT, it is crucial to enhance DLIT skills among individuals, including certified librarians, university librarians, and EFL learners, to meet academic and life goals, manage computer problems, and effectively use digital technologies (Sambo, Imran, Akanbi, & Education, 2022). However, there are challenges in implementing DLIT in teaching and learning activities, particularly in the classroom (Purmayanti, 2022). Factors affecting digital financial literacy, such as training, motivation, age, education level, and income, also play a role in shaping individuals' DLIT (Naufalin & Tohir, 2022). In conclusion, DLIT in the context of big data is a complex and multifaceted concept that encompasses various skills and competencies essential for individuals to navigate the digital world effectively. It is crucial for individuals to develop proficiency in DLIT to meet the demands of the digital society and effectively utilize big data.

DLIT is the most important skill of DL (Kane et al., 2019) because having the understanding of digital technologies provides and edge to leader to make accurate decision (Kane et al., 2019). Building DLIT among the employees is one of the responsibility of leadership (Khaw, Teoh, Abdul Khalid, & Letchmunan, 2022). DLIT allow employee to access the stakeholder to engage them, which enable them to respond more actively and effectively (W. Li, Liu, Belitski, Ghobadian, & O'Regan, 2016). Kane et al. (2019) also claims that DL can update the employee DLIT.

$H_{10}$: Digital leadership (DL) has a positive effect on digital literacy (DLIT).

## 2.24 Digital leadership, digital literacy and big data analytical capabilities

DLIT plays a crucial role in mediating the relationship between DL and BDAC's. Wang et al. (2022) highlight that DL positively influences exploratory innovation, with digital entrepreneurial orientation and organizational culture mediating this relationship. Moreover, the study suggests that the mediating effect is positively moderated by BDAC's. Similarly, Pilav-Velic et al. (2021) found that DLIT is linked to innovative work behavior through digital practices and attitudes towards digitalized innovation, indicating a mediating role of DLIT. Furthermore, Çallı et al. (2022) emphasize that the DLIT of executive managers mediates the relationship between generative leadership and digital maturity.

In the context of BDAC's, Wamba et al. (2017) propose a model that underlines the importance of BDAC's in enhancing firm performance. Additionally, Akter et al. (2016) explain how organizations can improve firm performance by aligning analytics capabilities with firm strategies, emphasizing the significance of having the required capabilities and strategic alignment. Moreover, Lozada et al. (2019) analyze the relationship between BDAC's and co-innovation, shedding light on the impact of these capabilities on innovation within organizations.

When considering the broader scope of DL and organizational capabilities, Saravanabhavan et al. (2020) discuss how big data and business analytics capabilities can lead to better decision-making and improved performance outcomes. Furthermore, Al-Darras and Tanova (2022) argue that BDAC's play a crucial role in developing organizational agility, which in turn creates value for firms and stakeholders. Additionally, Xiao et al. (2020) explore how the interaction between BDAC's and digital platform capabilities affects service innovation, emphasizing the importance of DC in driving innovation.

DL acts as a mediator between DL, BDAC's, and organizational outcomes. Organizations that effectively leverage DLIT, in conjunction with DL and BDAC's, are better positioned to drive innovation, enhance firm performance, and foster organizational agility.

Digital transforming capability of dynamic capability view has sub capability named improving digital maturity which represents DLIT through its components like identify digital workforce maturity, external recruiting of digital natives and leveraging digital knowledge inside firm (Warner & Wäger, 2019). All these characteristic signals towards employee DLIT. Kane et al. (2019) argue that DL is digitally literate and they discuss leadership role in effective way that when organization adopts new technologies for digital transformation, DL does empower employee with digital knowledge and skill for success. DLIT support leaders transformative vision and forward looking approach (Kane et al., 2019). Recent studies have studied employee DLIT role in digital transformation that how their literacy impact digital technologies usage (Cetindamar et al., 2021) unfortunately, employee DLIT influenced by DL and its effect on BDA is scant and future research is recommended to study impact of employee DLIT on big data (Cetindamar et al., 2021). Executives DLIT need to be updated because digital technologies like BDA are changing the business environment even more rapidly every day, therefore they have to become a sophisticated data scientist so that they can make more sophisticated decisions (Kane et al., 2019). Bases on these hypotheses current study proposed below hypothesis.

$H_{11}$: Digital literacy (DLIT) mediates the relationship between digital leadership (DL) and big data analytical capabilities (BDAC's.)

## 2.25 Digital leadership and industrial internet of things

The IIoT is about connecting all the industrial assets, including machines and control systems, with the information systems and the business processes (Sisinni, Saifullah, Han, Jennehag, & Gidlund, 2018). Navigating innovation ecosystems which is one of the sub-capability of digital transforming capability focused on digital ecosystem (Warner & Wäger, 2019). This ecosystem is constantly evolving and mainly depends upon mature IIOT in current study context. Current study suggests the transformation of business model, which means a transition from traditional way of value creation to digitalize way of value creation through BDAC's and it is main depends upon mature IOT (Warner & Wäger, 2019). DL is digitally literate and understand the technology and its usage, more importantly DL has the transformative vision (Kane et al., 2019). Therefore, DL will play its role in developing this digital ecosystem by participating into the IIOT platform. Warner and Wäger (2019) has identified a number of organizations who has reshaped their business model using IOT platform and they also suggested the DL for any digital transformation based on dynamic capability theory. Based on these arguments current study proposed below hypothesis.

$H_{12}$: digital leadership (DL) has a positive effect on matured industrial internet of things (IIOT).

## 2.26 Digital leadership, industrial internet of things and big data analytical capabilities

Digital transforming capabilities sub capabilities including joining digital ecosystem, interacting with multiple external partners and exploiting a new ecosystem capabilities are pointing towards interactions with partner, supplier and other stakes holder (Warner & Wäger, 2019). Recently Rajnoha and Hadač (2021) claimed that internet of things will play an effective role in development of informatics technology like BDA (Feng & Shanthikumar, 2018). Furthermore, Rajnoha and Hadač (2021) found that only significant to collect data through internet of things because data collected through such technology is dynamic and vibrant for sophisticated analysis in predicting and for big data decision making quality. Several studies have studies internet of things (Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash, 2015; Da Xu, He, & Li, 2014; Díaz, Martín, & Rubio, 2016; C. Liu, Yang, Zhang, & Chen, 2015). Internet of things also facilitate concept like real time operation, efficiently data utilization with BDA (Lv, Song, Basanta-Val, Steed, & Jo, 2017; Roden, Nucciarelli, Li, & Graham, 2017). DL being digital literate leader and know how these technologies works will invest in such technologies like IOT (Kane et al., 2019) and these technologies will help leader in their digital transformation. Based on these arguments current study proposed below hypothesis.

$H_{13}$: Industrial internet of things (IIOT) mediates the positive relationship between digital leadership (DL) and big data analytical capabilities (BDAC's).

## 2.27 Big data analytical capability and data driven decision making

Digital transformation encompasses the replacement of traditional business standards and perspectives with more contemporary, technology-driven approaches (Ghosh et al., 2021). This entails the replacement of business models, through which organizations create value and generate profits by managing structured, networked activities (Warner & Wäger, 2019; Zott et al., 2011). The transition from antiquated, traditional business models, characterized by value creation and profit generation through experiential (McAfee et al., 2012) and intuitive (Dane & Pratt, 2007) decision-making, to DDDM is a fundamental aspect of digital transformation. Decisions driven by BDA are rooted in insights derived from data, rather than relying on experience or intuition. This shift towards DDDM is expected to enhance organizational decision-making processes. DDDM is reliant on the capabilities of BDA (Janssen et al., 2017) but Digital transformation capability pertains to the organization's capacity to cultivate and implement novel digital competencies (Ghosh et al., 2021). Structured networked activities facilitate the interplay among organizational resources, including machinery, human capital, and control systems. This interaction is enabled by the application of analytical capabilities to data, a capability made feasible by the advancement of digital technologies. This, in turn, allows for proactive decision-making in business operations. (Ghosh et al., 2021). Rigorous decision-making techniques have been developed through the capabilities of BDA, which is currently more influential than other analytics methods previously employed (McAfee et al., 2012). Awan et al. (2021) posited that BDA capabilities play a pivotal role in the decision-making process. BDAC's is instrumental in creating value for organizations (Wixom, Yen, & Relich, 2013); Moreover, it harnesses management and talent capabilities, thereby generating additional business value that contributes to enhanced decision-making processes (Awan et al., 2021). In the context of big data, BDAC's have been accorded significant importance compared to big data decision-making, which is a broader concept encompassing various aspects beyond analytics. Shamim, Zeng, Shariq, and Khan (2019) asserted that the literature has yet to provide a definitive answer on how to enhance big data decision-making capabilities. Based on the arguments current study proposed below hypothesis.

$H_{14}$: Big data analytical capabilities (BDAC's) has a significant positive impact on data driven decision making (DDDM).

# 3. RESEARCH FRAMEWORK

After a detail discussion, that what the problem of research is research question and research objectives drive study towards a discussion about the interaction of several constructs with each other. Based on the discussion about the interaction of the constructs among each other, author proposed some hypothesis and depiction of the interaction among all the constructs and the hypothesis developed on the basis of detail discussion lead us towards below framework as depicted in Fig.2 below.

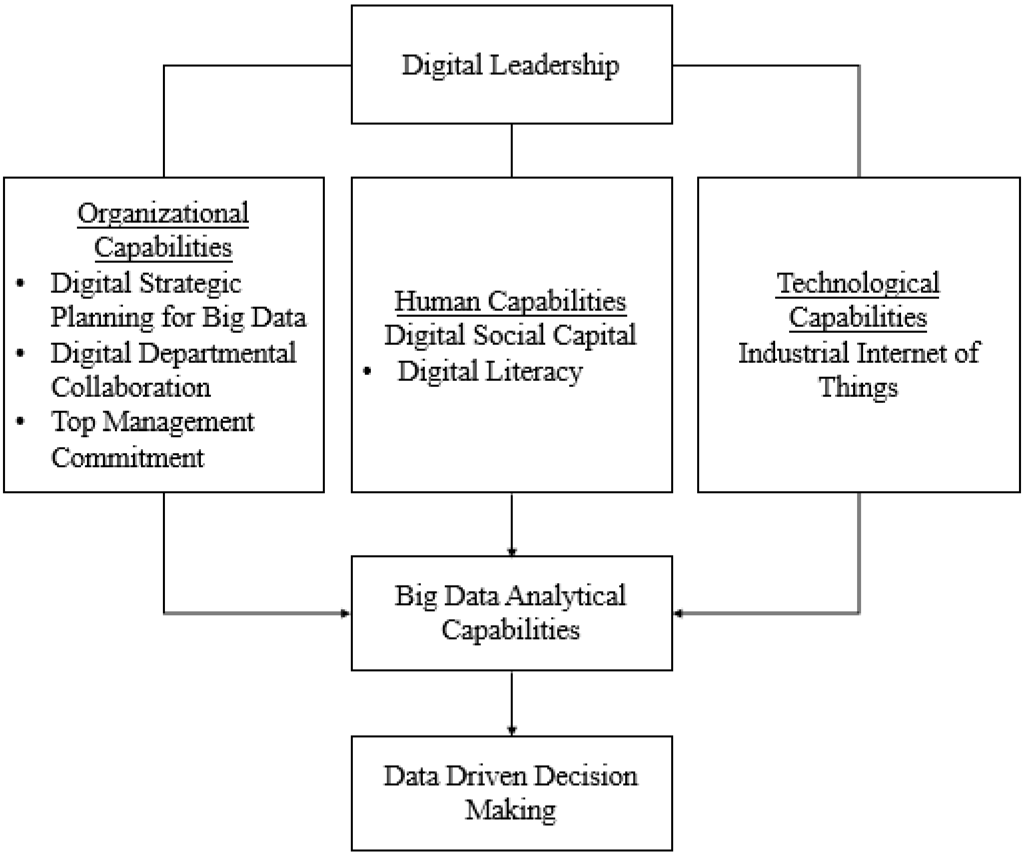


*Fig. 2: Research framework (Source: Author's own)*

# 4. PROPOSED METHODOLOGY

## 4.1 Research Philosophy

Research philosophy refers to the set of beliefs, principles, and assumptions that guide the research process. It shapes the researcher's worldview, influences their approach to collecting and interpreting data, and underpins the overall research design. There are three main research philosophies: positivism, interpretivism (or constructivism), and pragmatism.

## 4.2 Positivist Approach

Positivism assumes an objective reality that exists independently of human perception. It believes in the existence of a single, objective truth. Positivism is associated with an empirical, scientific approach to knowledge. It emphasizes the use of quantitative methods, experiments, and observation to discover regularities and patterns in the natural and social worlds. Positivist research is often deductive, involving hypothesis testing and the use of structured research instruments. It aims for generalizable and replicable findings.

## 4.3 Interpretivism Approach

Interpretivism acknowledges multiple realities and recognizes that reality is socially constructed. It emphasizes the subjective nature of human experiences. Interpretivism values the understanding of human behaviour in its natural context. It seeks to explore the meanings and interpretations individuals give to their experiences. Interpretive research often involves qualitative methods such as interviews, observations, and content analysis. It focuses on in-depth exploration, understanding, and context.

## 4.4 Pragmatism

Pragmatism is flexible in its ontological stance, recognizing that reality may be subjective or objective depending on the context. It emphasizes practical consequences. Pragmatism adopts a practical and problem-solving approach to knowledge. It values both qualitative and quantitative methods, selecting the most suitable approach based on the research question. Pragmatic research is characterized by its willingness to use mixed methods, combining qualitative and quantitative approaches as needed. The emphasis is on what works best to address the research problem.

These philosophical perspectives guide researchers in making decisions about the nature of reality, the ways they acquire knowledge, and the methods they employ in their research. It's important to note that the choice of research philosophy influences various aspects of the research process, including the research design, data collection methods, and data analysis techniques.

Current study adopt positivist, pragmatic research approach as this study is focus towards industry and profit making organizations. Deductive research approach is used which focused towards hypothesis development and quantitative analysis mainly. Survey strategy is applied using a structured questioner to collect data and the time horizon is cross sectional.

## 4.5 Sample Size Features

Sample size is a critical consideration in research design and data analysis. It refers to the number of observations or participants in a study. The size of the sample can have significant implications for the generalizability and reliability of the study results. Here are some key points to consider regarding sample size.

Representation of a larger sample size is generally better for achieving a representative sample of the population. A more representative sample increases the external validity of the study, allowing for more confident generalizations from the sample to the larger population.

Larger sample sizes lead to more precise estimates. The variability or margin of error in your findings tends to decrease with a larger sample, making your results more reliable and increasing the statistical power of your analysis.

Statistical power is the ability of a study to detect an effect or relationship if it exists. Larger sample sizes generally result in higher statistical power. This is crucial for detecting real effects, especially small or subtle ones.

The size of your sample affects how confidently you can generalize your findings to the entire population. A small sample may not be representative enough to make broad generalizations.

## 4.6 Population

For the purpose of data collection Pakistan is selected because in the south Asian region Pakistan is far beyond its neighbouring countries. China and India are the top players in digitalization or doing a digital business in China and India is easy. Doing digital business in Bangladesh is not easy as in India but the momentum of growth in Bangladesh is good whereas, Pakistan has shortcoming with digital capabilities along with the momentum of digital development (Chakravorti, Bhalla, & Chaturvedi, 2020; Chakravorti & Chaturvedi, 2019). So the population for current study are the seniors industrial managers of chemical sector in Pakistan involved in decision making process.

## 4.7 Sample Size

Data were from 277 senior personnel working in chemical sector in Pakistan including paint manufacturing firms and pharma companies. Sample size is calculated through online calculator (Soper, 2021) for structural equation models and also supported by Westland (2010). This sample size calculator calculates sample size after considering the number of variables, item and the probability level.

## 4.8 Sampling Techniques

Sampling techniques can be broadly categorized into two main types: probability sampling (random sampling) and non-probability sampling. Each type has its own advantages, disadvantages, and specific applications in research.

## 4.9 Probability Sampling (Random Sampling)

In a simple random sampling approach, each individual within the population is equally likely to be chosen for inclusion in the sample. Random selection is usually achieved using random number generators or a randomization process. This method guarantees that each member of the population has an equal likelihood of being included in the sample, thereby ensuring the sample is representative of the population.

In stratified random sampling, the population is partitioned into distinct subgroups or strata based on specific characteristics, and subsequent random samples are extracted from each stratum. It ensures representation from each subgroup, providing a more precise analysis of each stratum. Stratified random sampling captures variability within different strata, ensuring representation of all relevant subgroups but requires detailed knowledge of the population's characteristics.

In systematic random sampling, individuals are selected at regular intervals from a list after a random starting point has been determined. The first individual is chosen randomly, and then every next individual thereafter is included with a same gap. It is easy to implement, provides a degree of randomness but risk of periodicity if there is a pattern in the population list.

In cluster sampling, the population is partitioned into distinct clusters, and then a random sample of these clusters is chosen for analysis. All individuals within the chosen clusters are included. It is often use when it is impractical to list all members of the population individually. It is cost-effective for large and geographically dispersed populations but risk of intra-cluster similarity and variability within clusters may not be fully captured.

## 4.10 NON-Probability Sampling (Random Sampling)

In convenience sampling, individuals are selected based on their ease of access or availability. Researchers choose participants who are readily available or easy to reach. It is quick and convenient, suitable for exploratory or preliminary research. but may lead to a non-representative sample, and findings may not generalize well.

In purposive sampling, participants are chosen based on specific characteristics that are deemed relevant to the research question under investigation. Researchers purposefully select individuals who possess the desired traits or characteristics. It is useful for studying specific subgroups, expertise, or characteristics but with the limited generalizability to the broader population.

In quota sampling, researchers establish predetermined quotas for specific characteristics and then sample individuals who meet those criteria until the quotas are fulfilled. It guarantees a diverse sample by ensuring representation of specific subgroups with diversity in the sample but may introduce bias if the quotas are not well-defined.

In snowball sampling, participants are recruited through referrals from existing participants. The sample grows as each new participant refers others, creating a "snowball effect." It provide access to hard-to-reach populations, cost-effective, and rapid data collection but Sampling bias, lack of generalizability, and ethical considerations are some of its drawback.

## 4.11 Sampling Techniques Used

Current study focuses on non-probability sampling technique. Convenience sampling is used because at the beginning, we need some access towards our targeted population and we used snowball sampling technique because our study is discussing highly confidential maters like strategic planning, leadership style and decision making so it is hard to get response on these issue, this is the reason we used snowball sampling technique.

## 4.12 Data Collection Procedure

Before collecting data authors has provided surety to the respondent that there provided data will be kept secret and the data will not the analyzed neither on company basis nor there will be any comparison among the companies. Authors have make sure these issues in a way that the instrument that is used for data collection did not have the question neither related to the identity of the respondent nor the company.

Data collection procedure is proceeded by visiting sales and marketing managers during their visits at the sale points. Authors contacted them at the end of each month because this is the time when managers analyses their sales achievement versus sales target and plan more visits for the field to achieve sales target. Once data were collected from the sales manager, we request them to refer some other senior managers for data collection. Authors perform this activity at the end of the month and once a new month begins, we contact the same managers requesting to visit them at their office premises. Once we reach there, after a formal discussion we request them to give access and refer us to some other senior managers from different department including accounting and finance, distribution, supply chain, procurement and production. By this way, we manage to visit their head office, manufacturing plants and regional offices in Pakistan. We solicited responses from senior managers via a questionnaire, and then employed snowball sampling by asking respondents to refer us to additional potential participants. All respondents held key positions across various departments and were actively engaged in the decision-making process. Through this method, we successfully distributed a substantial number of questionnaires and conducted thorough follow-ups, we managed to receive 277 questionnaires. Study is a cross sectional study and structural equation modelling using SMARTPLS 3 is applied.

Reason for selecting SMARTPLS 3 is due to the reflective model of this study. Model in which the latent variables are the reflection of their item is called reflective model and there is a correlation in their item for such reflective model a SMARTPLS is preferred. While making the model in SMARTPLS, it is in the default setting of SMARTPLS that it consider the model as reflective. When we assign any indicator to the latent variable its arrow is pointed towards the indicator from the latent variable and it has to be change if your model is not reflective in this study a reflective model is used so the authors do not change the direction of arrows (Wong, 2013).

## 4.13 Measures

A seven-point Likert scale is used to measure the constructs through adapted scales. DL scale was initially consisted of six items adapted by Zeike, Bradbury, Lindert, and Pfaff (2019) but due to reliability issue three items were deleted and is then measured with three items. DDC scale was initially consisted on four items adapted from Wamba et al. (2017) but due to reliability parameters one item was deleted and finally measured with three items. The construct of BDAC's is assessed using a 15-item scale, which is subdivided into three sub-dimensions: infrastructure flexibility, management capabilities, and personal capabilities having three items each. This scale was adapted from a previous study by (Akter et al., 2016). Nine item are related to self-develop big data quality that is considered as an integral element of BDA in current study. Current study used four categories as indicators discussed above in DBAC's scale details that are infrastructure, management, personal capability and big data quality by taking the average of their relevant items.

TMC was initially consist of five items but due to reliability issue one item was dropped and the construct is measured with four items scale. DSP was initially consist of eleven items but due to reliability issue DSP is measured through a eight items and big data decision making is measured through seven item scale, two item were dropped due to reliability issue and these scales were adapted from El-Kassar and Singh (2019), Powell (1992) and Shamim et al. (2019) respectively. DLIT scale consist of five categories including information and DLIT, communication and collaboration, digital content creation, safety and problem solving. Each category consist of three item which mean fifteen items in total and these five categories are used as an indicator in software for measuring DLIT by taking the average of these three items, scale adapted from Cetindamar et al. (2021). DSC is measured using 10 item scale used by ul zia et al. (2022), scale includes items related to structural, relational and cognitive social capital having three, four and three items respectively. IIOT is measured using a four item scales adapted from (Dijkman, Sprenkels, Peeters, & Janssen, 2015). All the non-categorized scales including DL, TMC, DSP, DDC IIOT, DSC and DDDM is represented in Table.1 whereas, categorical scale including BDAC's and DLIT is represented in Table.2

Table.1 Coding details of question for analysis

| Construct | Code | Question or Indicator |
|---|---|---|
| DL | 4 | Our leadership is driving the digital transformation forward proactively in our unit. |
| | 5 | Our leadership can make others enthusiastic about the digital transformation. |
| | 6 | Our leadership has a clear idea of the structures and processes that are needed for the digital transformation. |
| TMC | 7 | Our organization's top management expresses how big data partnering will provide significant business benefits to the firm. |
| | 8 | Our organization's top management expresses how big data partnering will create a significant competitive arena. |

| | | |
|---|---|---|
| | 9 | Our organization's top management articulates collaborative vision for big data. |
| | 10 | Our organization's top management stablishes the metrics to monitor big data utilization success through partnering. |
| | 11 | Our organization's top management formulates big data related strategies for organizational information sharing. |
| DDC | 13 | In our organization, business analysts and line people from various departments regularly attend cross-functional meetings using digital platform to discuss important issues related to big data. |
| | 14 | In our organization, business analysts and line people coordinate their big data related efforts harmoniously through digital platform. |
| | 15 | In our organization, information is widely shared between business analysts and line people using digital platform so that those who make decisions or perform jobs have access to all available know-how related to big data. |
| DSP | 16 | Our organization have broad, long-range big data related goals known to all managers (GOALS). |
| | 17 | Our organization have specific, short-term big data related goals known to all managers (GOALS). |
| | 19 | Our organization have a department devoted exclusively to big data related planning (ANALYS). |
| | 21 | Our organization use mathematical and computer models as big data related planning aids (ANALYS). |
| | 22 | Our organization have a written big data related plan for the next 12 months (ANALYS). |
| | 23 | Our organization's big data related planning outlook is more long-term than short-ter (ANALYS). |
| | 25 | Our organization use special market research studies (SCANING). |
| | 26 | Our organization search systematically for new products (SCANNG). |
| DDDM | 45 | We believe that our organization make good decisions based on the data. |

| | | |
|---|---|---|
| | 46 | The data based decisions which our organization make result in the desired outcomes. |
| | 47 | Our organization is satisfied with the outcomes of its data based decisions. |
| | 48 | Our organization's decisions based on the data improve organisational performance. |
| | 50 | Our organization's databased decision-making cost is very low. |
| | 52 | Our organization do not need a lot of people to make decisions based on the data. |
| | 53 | Our organization make timely decisions based on the data. |
| IOT | 54 | In my opinion, IIoT technology will be applied mainly for business-to-business markets instead of business to consumer markets. |
| | 55 | In my opinion, IIoT technology will be used mainly to offer services instead of products |
| | 56 | In my opinion, the data gained from IIoT will be used to create additional value for revenue generation in the future |
| | 57 | In my opinion, the partner structure of IIoT product's business models is more complex than the partner structure of business models of conventional products |
| DSC | 74 | Our relationship departments uses digital technologies to know what knowledge we have at our disposal |
| | 76 | We feel connected to our business partners through digital technologies. |
| | 77 | We know our business partners will always try and help us out through digital technologies if we get into difficulties |
| | 78 | We can trust our business partners to lend us a hand through digital technologies if we need it |
| | 79 | We can rely on our business partners when we need support in our work based on digital technologies. |
| | 80 | Our business partners and we always agree on what is important at work |

| | | |
|---|---|---|
| | 81 | Our business partners and we always share the same ambitions and vision related to digitalization at work. |
| | 82 | Our business partners and we are always enthusiastic about pursing the collective goals and missions related to digitalization of the whole organization. |

*(Source: Author's own)*

Table.2 Coding details for categorized scale

| Construct | Category code | Item Code | Question or indicator or Item |
|---|---|---|---|
| DLIT | CC | 61 | I actively use a wide range of online communication tools at work. |
| | | 62 | I choose digital tools and technologies for collaborative processes. |
| | | 63 | I have net-etiquette (differentiate behavioural norms) while using CT and interacting in digital environments. |
| | DCC | 64 | I can produce complex digital content in different formats. |
| | | 65 | I can apply advanced formatting functions of different tools to the content others or I have produced. |
| | | 66 | I respect copyright and license rules and I know how to apply them to digital information and content. |
| | Safety | 67 | I am able to apply advanced settings to some software and programs. |
| | | 68 | I periodically check my privacy settings and update my security programs on the devices that I use to access the internet |
| | | 69 | I am able t select safe and suitable digital media, which are efficient and cost-effective in comparison with others. |

| | | | |
|---|---|---|---|
| | Problem Solving | 70 | I am able to solve a technical problem or decide what to do when technology does not work. |
| | | 71 | I can use digital technologies to solve problems. |
| | | 72 | I am able to use varied media to express myself creatively. |
| BDAC's | MGT | 27 | Our organization continuously examine innovative opportunities for the strategic use of big data analytics. |
| | | 28 | Our organization enforce plans for the introduction and of big data analytics adequately. |
| | | 29 | Our organization enforce plans for the utilization of big data analytics adequately. |
| | INF | 30 | Our organization perform big data analytics planning processes in systematic ways. |
| | | 31 | Our organization perform big data analytics planning processes in formalized ways. |
| | | 32 | Our organization frequently adjust big data analytics plans to better adapt to changing conditions. |
| | PRS | 33 | When our organization make big data analytical investment decisions, it consider and project about how much these options will help end-users make quicker decisions. |
| | | 34 | In our organization, business analysts and line people frequently meet to discuss important issues formally. |
| | | 35 | In our organization, business analysts and line people frequently meet to discuss important issues informally. |
| | QLTY | 36 | The data our organization use, reflect high level of accuracy. |
| | | 37 | Our organization do not face problems in decision-making due to accuracy of data. |
| | | 38 | In our organization, new data replace the old data in timely manner. |

| | | | |
|---|---|---|---|
| | | 39 | In our organization, data is regularly updated according to changes happening in business environment. |
| | | 40 | We often face problems in decision-making due to incomplete data. |
| | | 41 | Our data do not contains a lot of irrelevant details. |
| | | 42 | Our data is formatted in a precise manner for decision-makers. |
| | | 43 | Our data reflect high level of relevance with our business operations. |
| | | 44 | Our data are useful for our business decision-making. |

*(Source: Author's own)*

# 5. RESULTS OF RESEARCH

In current chapter we will discuss the reliability and validity issues of the model furthermore, we will also discuss the R squares, path coefficient of the variable and in the last we will discuss the proposed hypothesis.

## 5.1 Reliability And Validity

For the purpose of hypothesis testing following thing should be discussed be discussed in order to confirm the reliability and validity of the data.

1. Outer model loading
2. Indicator reliability
3. Internal consistent reliability/ composite reliability
4. Convergent validity AVE
5. Discriminant validity

All of these reliability and validity issues must have to be discussed before detailed analysis, what are the values generated in smart PLS and what are the minimum criteria which is referred by smart PLS and some other studies

## 5.2 Outer Model Loading

Outer model loading values is gathered after generating the default report of PLS algorithm. Loading score represents the correlation between items and construct. The highest outer loading value is 0.96 that relates to DL and the lowest outer loading value is 0.7 that is related to DDC. All other outer loading values lies in between these two value. A pictorial overview of the indicators loading scores is reflected in fig 3 (with indicators). Secondly an overall model excluding indicators are depicted in fig 4.

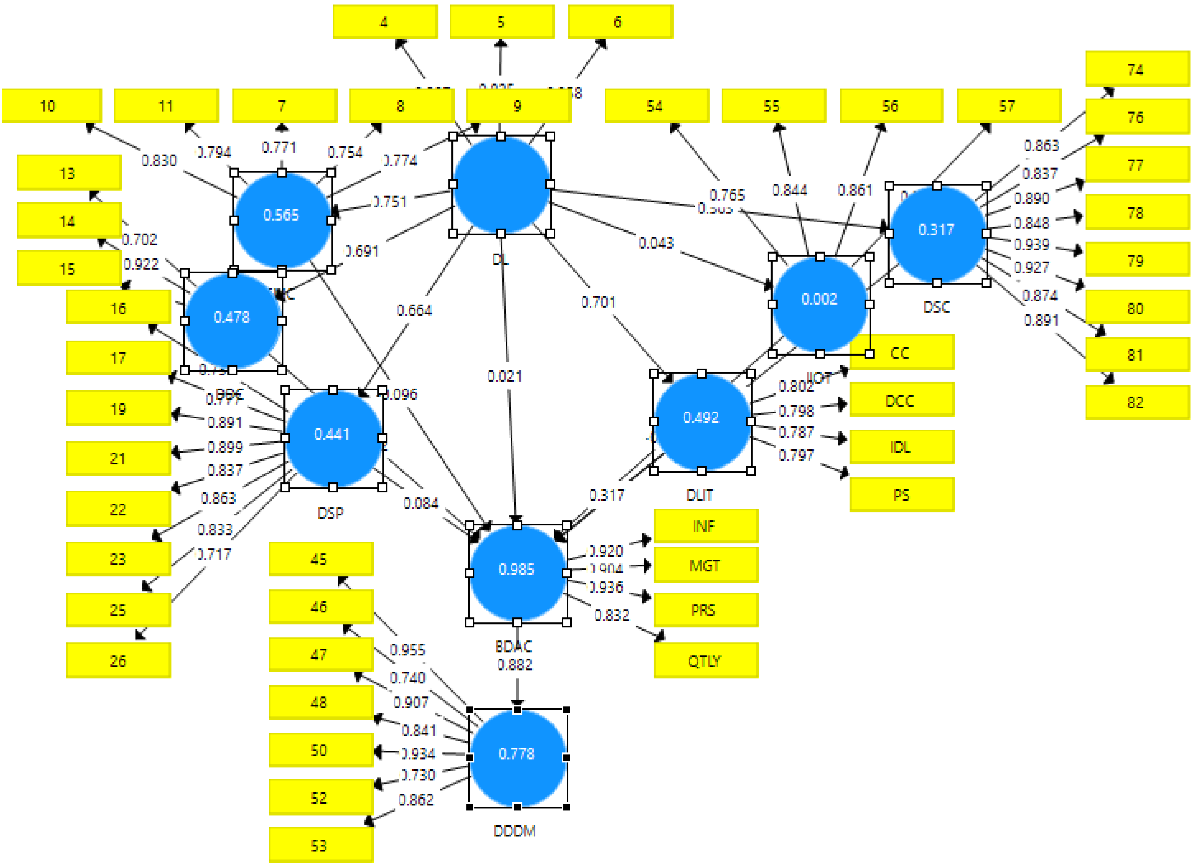


*Fig 3 Path algorithm with indicators (Source: Author's own)*

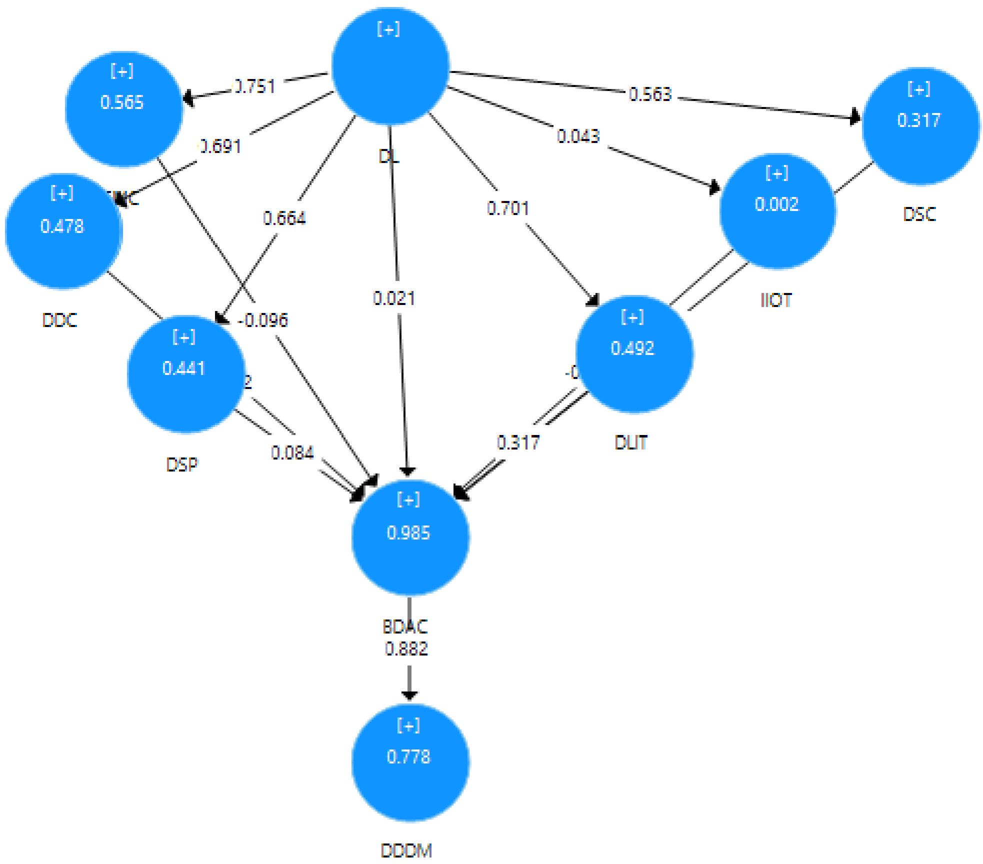


*Fig 4 Path algorithm without indicators (Source: Author's own)*

## 5.3 Indicator Reliability

Indicators reliability tells us that how much an indicator or item is representing or supporting their latent variable individually. Indicator reliability refers to the extent to which individual items or indicators in a measurement instrument accurately and consistently measure the underlying construct they are intended to represent. This concept is particularly important in the context of structural equation modeling (SEM) and confirmatory factor analysis (CFA), where researchers often work with latent constructs measured by multiple observed variables or indicators. The value of indicator reliability should be 0.7 or above but if the study is an exploratory study than 0.4 is also acceptable (Hulland, 1999).It is calculated by taking the square of loadings values. Indicator reliability for all the item are above the minimum required values and presented in table 3.

## 5.4 Composite Reliability

Composite reliability shows the value that how much indicators or items represent or support their latent variable jointly. However cronbach alpha is also provided by the software but it is suggested that not to report that reliability must be reported through composite reliability (Wong, 2013). Its value must be 0.7 but 0.6 is also acceptable if the study is an exploratory study (Bagozzi & Yi, 1988). It is derived from the default report after running PLS algorithm.

Composite reliability for DSC has the highest value among all that is 0.97 that means that the items of DSC is supporting their latent variable by 97%. The lowest composite reliability value is of DLIT, which is 0.87 which means that latent variable of DLIT is getting 87% of support from their indicators. Other constructs including DL, TMC, DDC, DSP, DDDM, IIOT and BDAC has a composite reliability value of 0.93, 0.89, 0.9, 0.94, 0.95, 0.92 and 0.94 respectively. It means that DL is getting a support of 93% from its relevant indicators; TMC is getting a support of 89% from its relevant indicators; DDC is getting a support of 90% from its relevant indicators; DSP is getting a support of 94% from its relevant indicators; DDDM is getting a support of 95% from its relevant indicators; IIOT is getting a support of 92% from its relevant indicators and BDAC is getting a support of 94% from its relevant indicators. All these value and outcomes are shone in table 3.

## 5.5 Convergent Validity

Convergent validity or AVE values are generated by same criteria as the value of composite reliability was derived. It is suggested that its value should be 0.5 or above (Bagozzi & Yi, 1988). Researchers use convergent validity to provide evidence that a particular indicator is indeed assessing the intended construct. If two measures of the same construct are strongly correlated, it suggests that they are converging on the same underlying concept. Convergent validity is typically assessed by examining the correlation coefficient between scores on two different indicators. A high correlation suggests good convergent validity, while a low correlation may indicate a lack of convergence. The minimum convergent validity value for current study construct is 0.62 and the maximum value is 0.81, which is reflected in table 3.

Table.3 Reliability and validity

| Variable | Item | Outer Loading | Item Reliability | Composite Reliability | Cronbach's Alpha | rho_A | AVE |
|---|---|---|---|---|---|---|---|
| DL | 4 | 0.91 | 0.83 | 0.93 | 0.88 | 0.93 | 0.81 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 5 | 0.83 | 0.69 | | | | |
| | 6 | 0.96 | 0.92 | | | | |
| TMC | 7 | 0.77 | 0.59 | 0.89 | 0.84 | 0.85 | 0.62 |
| | 8 | 0.75 | 0.56 | | | | |
| | 9 | 0.77 | 0.59 | | | | |
| | 10 | 0.83 | 0.69 | | | | |
| | 11 | 0.79 | 0.62 | | | | |
| DDC | 13 | 0.7 | 0.49 | 0.9 | 0.82 | 0.84 | 0.74 |
| | 14 | 0.92 | 0.85 | | | | |
| | 15 | 0.94 | 0.88 | | | | |
| DSP | 16 | 0.73 | 0.53 | 0.94 | 0.93 | 0.93 | 0.68 |
| | 17 | 0.78 | 0.61 | | | | |
| | 19 | 0.89 | 0.79 | | | | |
| | 21 | 0.9 | 0.81 | | | | |
| | 22 | 0.84 | 0.71 | | | | |
| | 23 | 0.86 | 0.74 | | | | |
| | 25 | 0.83 | 0.69 | | | | |
| | 26 | 0.72 | 0.52 | | | | |
| DDDM | 45 | 0.96 | 0.92 | 0.95 | 0.94 | 0.95 | 0.73 |
| | 46 | 0.74 | 0.55 | | | | |
| | 47 | 0.91 | 0.83 | | | | |
| | 48 | 0.84 | 0.71 | | | | |
| | 50 | 0.93 | 0.86 | | | | |
| | 52 | 0.73 | 0.53 | | | | |
| | 53 | 0.86 | 0.74 | | | | |
| IIOT | 54 | 0.76 | 0.58 | 0.92 | 0.89 | 1.38 | 0.73 |
| | 55 | 0.84 | 0.71 | | | | |
| | 56 | 0.86 | 0.74 | | | | |
| | 57 | 0.95 | 0.90 | | | | |
| DSC | 74 | 0.86 | 0.74 | 0.97 | 0.96 | 0.96 | 0.78 |
| | 76 | 0.84 | 0.71 | | | | |
| | 77 | 0.89 | 0.79 | | | | |
| | 78 | 0.85 | 0.72 | | | | |
| | 79 | 0.94 | 0.88 | | | | |
| | 80 | 0.93 | 0.86 | | | | |
| | 81 | 0.87 | 0.76 | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 82 | 0.89 | 0.79 | | | | |
| DLIT | Communication and collaboration | 0.8 | 0.64 | 0.87 | 0.81 | 0.81 | 0.63 |
| | Digital content creation | 0.8 | 0.64 | | | | |
| | Problem solving | 0.8 | 0.64 | | | | |
| | Information and data literacy | 0.79 | 0.62 | | | | |
| BDAC | Infrastructure | 0.92 | 0.85 | 0.94 | 0.92 | 0.92 | 0.81 |
| | Management | 0.9 | 0.81 | | | | |
| | Personal | 0.94 | 0.88 | | | | |
| | Big data quality | 0.83 | 0.69 | | | | |

*(Source: Author's own)*

## 5.6 Discriminant validity

It is essential to confirm discriminant validity, as without it, the credibility and confidence of the results and their implications may be compromised. Discriminant validity is established by examining the correlations among constructs. If the diagonal (bold) numbers at the top of each column are higher than the other numbers in the columns, discriminant validity is said to be confirmed. The diagonal numbers, which are derived from the square root of convergent validity, are higher than the other numbers in the rows and columns in this study. Therefore, the discriminant validity of the data involved in this study is confirmed and represented in table 4.

Table.4 Discriminant validity

| BDAC | DDC | DDDM | DL | DLIT | DSC | DSP | IIOT | TMC |
|---|---|---|---|---|---|---|---|---|
| **0.9** | | | | | | | | |
| 0.59 | **0.86** | | | | | | | |
| 0.88 | 0.52 | **0.86** | | | | | | |
| 0.62 | 0.69 | 0.51 | **0.9** | | | | | |
| 0.85 | 0.66 | 0.84 | 0.7 | **0.8** | | | | |
| 0.71 | 0.51 | 0.85 | 0.56 | 0.7 | **0.88** | | | |
| 0.8 | 0.68 | 0.73 | 0.66 | 0.79 | 0.76 | **0.82** | | |
| 0.03 | 0.06 | 0.04 | 0.04 | 0.04 | 0.03 | 0.05 | **0.86** | |
| 0.72 | 0.73 | 0.67 | 0.75 | 0.76 | 0.7 | 0.81 | 0.04 | **0.78** |

*(Source: Author's own)*

## 5.7 R SQUARE Or Coefficient of Determination

R-squared ($R^2$) in the context of structural equation modeling (SEM), including the use of software like SmartPLS 3, is a measure of the proportion of variance in the endogenous latent variables that is explained by the model. In SmartPLS 3,

R-squared is often referred to as the "Coefficient of Determination."

The R-squared value ranges from 0 to 1, with 0 indicating that the model does not explain any variance in the endogenous latent variable, and 1 indicating that the model perfectly explains all the variance. Higher R-squared values suggest that the structural model accounts for a larger proportion of the variance in the endogenous latent variable. In other words we may say that the variation in any variable due to other latent variable is reflected in R squares value.

In table 5, R squares value are being represented where in it depicted that the highest variation in any construct is of 0.99 and is of BDAC, May the reason behind this is the highest number of construct effecting the construct of BDAC. DDDM is having R square value of 0.78 that is the second highest value in the model highest value in the model whereas, other construct including DDC, DLIT, DSC, DSP and TMC have the R square value of 0.48, 0.49, 0.32, 0.44 and 0.56 respectively. Lastly IIOT has an R square value of 0 which means that its dependent variable has no effect on it and this is the lowest value we have in current model.

Table.5 R square

| Construct | R Square | Adjusted R Square |
|---|---|---|
| BDAC | 0.99 | 0.98 |
| DDC | 0.48 | 0.48 |
| DDDM | 0.78 | 0.78 |
| DLIT | 0.49 | 0.49 |
| DSC | 0.32 | 0.31 |
| DSP | 0.44 | 0.44 |
| IIOT | 0 | 0 |
| TMC | 0.56 | 0.56 |

*(Source: Author's own)*

## 5.8 Path coefficient

In structural equation modeling (SEM), a path coefficient is a standardized regression coefficient that represents the strength and direction of the relationship between two latent variables. A unidirectional path in the structural model connects these latent variables. Path coefficients are crucial for understanding the hypothesized causal relationships between variables in the model. A path coefficient, denoted by the symbol β (beta), represents the effect of an independent latent variable (predictor) on a dependent latent variable (outcome) in the structural model. The sign of the path coefficient indicates the direction of the relationship (positive or negative), and the magnitude represents the strength of the relationship. A larger absolute value suggests a stronger association.

In current study BDAC has the highest number of construct that are effecting it. As depicted in table 6, DSC is affecting BDAC with a coefficient value of 0.668 that is the highest coefficient value in the model. The second highest coefficient value for BDAC is 0.317 and is coming through the DLIT. Other construct including DDC, DL and DSP has a coefficient value of 0.032, 0.021 and 0.084 respectively. Whereas IIOT and TMC has negative coefficient value that is -0.001 and -0.096 respectively that represents a negative correlation among them.

Table.6 Path coefficient value for BDAC

| Construct | BDAC |
|---|---|
| DDC | 0.032 |
| DL | 0.021 |
| DLIT | 0.317 |
| DSC | 0.668 |
| DSP | 0.084 |
| IIOT | -0.001 |
| TMC | -0.096 |

*(Source: Author's own)*

Path coefficient value for the dependent values of the construct DL is reflected in table 7. DL has the highest effect value of 0.751 that is for TMC followed by the effecting value of 0.701 that is for DLIT. DL is effecting DDC and DSP with a coefficient value of 0.691 and 0.664 respectively. Other coefficient value are 0.021, 0.563 and 0.043 for BDAC, DSC and IIOT respectively.

Table.7 Path coefficient values from DL

| Construct | DL |
|---|---|
| BDAC | 0.021 |
| DDC | 0.691 |
| DLIT | 0.701 |
| DSC | 0.563 |
| DSP | 0.664 |
| IIOT | 0.043 |
| TMC | 0.751 |

*(Source: Author's own)*

## 5.9 Hypothesis Testing

SmartPLS (Partial Least Squares) is a software tool used for structural equation modeling (SEM), which is a statistical method that examines relationships between variables. In the context of SmartPLS, hypothesis testing is often conducted to assess the significance of paths between variables and to evaluate the overall model fit. In SEM, hypotheses typically revolve around the relationships between latent variables. We have to set up your structural model in SmartPLS by defining the latent variables, their indicators, and the paths between them. SmartPLS uses the partial least squares algorithm to estimate the model parameters. This involves finding the path coefficients that best explain the relationships between latent variables. SmartPLS relies on bootstrapping as a resampling technique to assess the significance of the estimated path coefficients. Bootstrapping generates multiple resamples from the dataset, and the model is estimated for each resample. After bootstrapping, SmartPLS provides information about the significance of path coefficients. This information is often presented in the form of t-values, p-values, and confidence intervals.

In table 8 and 9 concept including β, SD, T value and UL and LL is discuss lets have a look that how they are and what they are informing us.

Beta values are associated with the path coefficients in the context of structural equation modeling (SEM). SmartPLS is a software tool used for partial least squares (PLS) structural equation modeling.

In the structural model of an SEM, the beta values represent the path coefficients between latent variables. These coefficients indicate the strength and direction of the relationships between the latent variables in the model.

In the structural model, paths are specified between latent variables, and the strength of these paths is quantified by path coefficients. These path coefficients are often denoted as beta values (β).

Each beta value represents the standardized coefficient of the relationship between two latent variables. Standardized coefficients are used to compare the relative importance of different paths in the model.

A positive beta value indicates a positive relationship between the two latent variables, suggesting that an increase in one variable is associated with an increase in the other.

A negative beta value indicates a negative relationship, suggesting that an increase in one variable is associated with a decrease in the other.

The magnitude of the beta value indicates the strength of the relationship. Larger absolute values suggest stronger relationships.

Standard deviation is a measure of the amount of variation or dispersion in a set of values. It quantifies the extent to which individual data points in a dataset differ from the mean (average) of the dataset. A low standard deviation indicates that the data points tend to be close to the mean, while a high standard deviation indicates that the data points are spread out over a large range of values.

There are eight direct relations in current study model, among them the strongest effect is of BDAC's on DDDM having a β value of 0.882 representing H14. β value reflect the effect size from one variable to another. 0.882 means that an increase of one unit in BDAC's will result as an increase of 0.882 units in DDDM. SD for this relationship is 0.01. A standard deviation of 0.01 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicate a higher level of confidence in the precision of the data.

Whereas, confidence interval for this relationship is the highest among all the relationships or hypothesis. Lower limit value for this relationship is 0.854 and the upper limit for this relationship is 0.905. Both these value are the highest lower limit and upper limit value in the whole model.

T value should be greater than 1.96 and if the T value is > than 1.96 it mean the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

For the above discuss relationship t value is 63.72 that is > 0.58, which means the p value for this relationship is < 0.001. This indicates the direct positive effect of BDAC's on DDDM that mean that the organizations who got better BDAC's are good in DDDM.

H6 has the second strongest effect is of DL on TMC having a β value of 0.751 representing H6. β value reflect the effect size from one variable to another. 0.751 means that an increase of one unit in DL will result as an increase of 0.751 units in TMC. SD for this relationship is 0.02. A standard deviation of 0.02 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicate a higher level of confidence in the precision of the data.

Whereas, confidence interval for this relationship is the second highest among all the relationships or hypothesis. Lower limit value for this relationship is 0.706 and the upper limit for this relationship is 0.788. Both these value are the second highest lower limit and upper limit value in the whole model.

T value should be greater than 1.96 and if the T value is > than 1.96 it mean the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H6 has the t value of 36.47, which is against the second highest t value after H16, which is > 0.58, which means the p value for this relationship is < 0.001. These results indicate a direct positive effect of DL on TMC that means organizations should led through a DL in order to enhance TMC.

H10 has the third strongest effect, which is of DL on DLIT having a β value of 0.701 representing H10. β value reflect the effect size from one variable to another. 0.701 means that an increase of one unit in DL will result as an increase of 0.751 units in DLIT. SD for this relationship is 0.03. A standard deviation of 0.03 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.637 and the upper limit for this relationship is 0.751. Both these values are according to the set parameter.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H10 has the t value of 24.46, which means the p value for this relationship is < 0.001. These results indicate the direct positive effect of DL on DLIT that means DLIT enhancement rely on DL. Organizations should focus towards DL to enhance the DLIT of employees.

H4 has the fourth strongest effect is of DL on DDC having a β value of 0.691 representing H4. β value reflect the effect size from one variable to another. 0.691 means that an increase of one unit in DL will result as an increase of 0.691 units in DDC. SD for this relationship is 0.02. A standard deviation of 0.02 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.643 and the upper limit for this relationship is 0.73. Both these values are according to the set parameter.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H4 has the t value of 31.49, which means the p value for this relationship is < 0.001. These results indicate the direct positive effect of DL on DDC. Through effective utilization of digital skills and capabilities of DL organization can improve their DDC in their organizations.

H2 has the fifth strongest effect is of DL on DSP having a β value of 0.664 representing H2. β value reflect the effect size from one variable to another. 0.664 means that an increase of one unit in DL will result as an increase of 0.691 units in DSP. SD for this relationship is 0.03. A standard deviation of 0.03 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.606 and the upper limit for this relationship is 0.718. Both these value are according to the set parameter.

T value should be greater than 1.96 and if the T value is > than 1.96 it mean the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H2 has the t value of 23.41, which means the p value for this relationship is < 0.001. These results indicate the direct positive effect of DL on DSP that means the organizations should take advantage of the digitalized vision of DL to formulate a DSP.

H8 has the sixth strongest effect is of DL on DSC having a β value of 0.563 representing H8. β value reflect the effect size from one variable to another. 0.563 means that an increase of one unit in DL will result as an increase of 0.563 units in DSC. SD for this relationship is 0.04. A standard deviation of 0.04 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.482 and the upper limit for this relationship is 0.633. Both these values are according to the set parameter.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H8 has the t value of 14.62, which means the p value for this relationship is < 0.001. This indicates a direct positive effect of DL on DSC that means the organization who are trying to strengthen relations through DSC for the betterment of the firm must be lead through DL. DL having a strong understanding of digital technologies takes full advantages of digital platform to enhance DSC for the firm.

H12 has the seventh strongest effect is of DL on IIOT having a β value of 0.043 representing H12. β value reflect the effect size from one variable to another. 0.043 means that an increase of one unit in DL will result as an increase of 0.043 units in IIOT. SD for this relationship is 0.09. A standard deviation of 0.09 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicate a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is -0.167 and the upper limit for this relationship is 0.145. Both these values are not according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H8 has the t value of 0.50, which means the p value for this relationship is > 0.005. This indicates a shortcoming in applying the sample results to the whole population therefore H8 is rejected. Author interpret this in such a way that DL is not effecting or not enough capable to enhance IIOT as it is needed.

H1 has the eight strongest effect is of DL on BDAC having a β value of 0.021 representing H1. β value reflect the effect size from one variable to another. 0.021 means that an increase of one unit in DL will result as an increase of 0.021 units in BDAC. SD for this relationship is 0.01. A standard deviation of 0.01 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is -0.007 and the upper limit for this relationship is 0.049. Both these values are not according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H1 has the t value of 1.46, which means the p value for this relationship is > 0.005. This indicates a rejection of H1. Results should not be implemented on the whole population due to higher P value. It represents a strong need of mediators or means through which DL can enhance BDAC's.

Table.8 Hypothesis Testing

| Hypothesis | Relationship | β | SD | T Value | LL (2.5%) | UL (97.5%) | Result |
|---|---|---|---|---|---|---|---|
| H1 | DL -> BDAC | 0.021 | 0.01 | 1.46 | -0.007 | 0.049 | Rejected |
| H2 | DL -> DSP | 0.664 | 0.03 | 23.41 | 0.606 | 0.718 | Accepted |
| H4 | DL -> DDC | 0.691 | 0.02 | 31.49 | 0.643 | 0.73 | Accepted |
| H6 | DL -> TMC | 0.751 | 0.02 | 36.47 | 0.706 | 0.788 | Accepted |
| H8 | DL -> DSC | 0.563 | 0.04 | 14.62 | 0.482 | 0.633 | Accepted |
| H10 | DL -> DLIT | 0.701 | 0.03 | 24.46 | 0.637 | 0.751 | Accepted |
| H14 | BDAC -> DDDM | 0.882 | 0.01 | 63.72 | 0.851 | 0.905 | Accepted |
| H12 | DL -> IIOT | 0.043 | 0.09 | 0.50 | -0.167 | 0.145 | Rejected |

*(Source: Author's own)*

## 5.10 Mediation analysis

Baron and Kenny (Baron & Kenny, 1986) introduced a widely cited and influential procedure for testing and establishing mediation in a statistical model. The Baron and Kenny mediation analysis involves several steps. Here's a casual procedure based on their original work:

First step is to establish a significant relationship between the independent variable and the dependent variable. This is typically done through regression analysis. Next step is to establish a significant relationship between independent variable and the mediator. Third step is to establish a significant relationship between mediator and dependent variable. This is done through regression analysis as well. Forth and the last step is to combine independent variable and mediating variable to predict dependent variable. If the previous significant relationship between independent variable and dependent variable become insignificant after the intervention of mediating variable, it suggest mediation.

Preacher and Hayes (2004); (Preacher & Hayes, 2008) Bootstrapping is a resampling technique used to estimate the sampling distribution of a statistic by repeatedly resampling, with replacement, from the observed data. Bootstrapping is commonly employed in mediation analysis to obtain more accurate confidence intervals for the indirect effects. This method is also supported by (Hair Jr, Hult, Ringle, & Sarstedt, 2016).

After running the bootstrapping process, SMARTPLS3 generated results that are reflected in Table 9. Which are further discussed in detail. A pictorial overview is also provided in fig 5 (with indicator) and fig 6 (without indicator).

H9 has the strongest mediating effect of DSC on the relationship between DL and BDAC having a β value of 0.376 representing H9. β value reflect the effect size from one variable to another. 0.376 means that an increase of one unit in DL and DSC will result as an increase of 0.376 units in BDAC. SD for this relationship is 0.027. A standard deviation of 0.027 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.323 and the upper limit for this relationship is 0.428. Both these values are according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H9 has the t value of 14.20, which means the p value for this relationship is > 0.005. This reflects a mediation of DSC between DL and BDAC’s. H1 is rejected because there was not relationship between DL and BDAC’s but H9 is supported that claims the mediating role of DSC between DL and DSC. DL should focused towards desired outcomes but they should not ignore the means through which desired outcomes would become achievable.

H11 has the second strongest mediating effect of DLIT on the relationship between DL and BDAC having a β value of 0.222 representing H11. β value reflect the effect size from one variable to another. 0.222 means that an increase of one unit in DL and DLIT will result as an increase of 0.222 units in BDAC. SD for this relationship is 0.017. A standard deviation of 0.017 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.189 and the upper limit for this relationship is 0.255. Both these values are according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H11 has the t value of 13.11, which means the p value for this relationship is > 0.001. Based on all these values discussed above including confidence internal value and the t value H11 is accepted. This indicates the importance of DLIT. High level of DLIT in employee will results as high level BDAC's for the organization.

H3 has the third strongest mediating effect of DSP on the relationship between DL and BDAC having a β value of 0.056 representing H3. β value reflect the effect size from one variable to another. 0.056 means that an increase of one unit in DL and DSP will result as an increase of 0.056 units in BDAC. SD for this relationship is 0.011. A standard deviation of 0.011 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.033 and the upper limit for this relationship is 0.077. Both these values are according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H3 has the t value of 4.99, which means the p value for this relationship is > 0.001. This indicates a mediating role of DSP between DL and BDAC's. DL formulates a DSP which suits the desired outcome so that DL and DSP jointly influence the BDAC's. DL should focuse on the means through which they are going the achieve their desired outcomes.

H5 has the third strongest mediating effect of DDC on the relationship between DL and BDAC having a β value of 0.022 representing H5. β value reflect the effect size from one variable to another. 0.022 means that an increase of one unit in DL and DDC will result as an increase of 0.022 units in BDAC. SD for this relationship is 0.008. A standard deviation of 0.008 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is 0.005 and the upper limit for this relationship is 0.036. Both these values are according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it mean the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H5 has the t value of 2.83, which means the p value for this relationship is > 0.001. This indicates a mediating role of DDC between DL and BDAC's. DDC plays a vital role in enhancement of BDAC's along with DL. Collaborative and DLIT of DL help him in formulating a strong DDC among the departments which results as enhanced BDAC's.

H7 has the mediating effect of TMC on the relationship between DL and BDAC having a β value of -0.072 representing H7. β value reflect the effect size from one variable to another. -0.072 means that an increase of one unit in DL and TMC will result as a decrease of 0.072 units in BDAC. SD for this relationship is 0.012. A standard deviation of 0.012 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is -0.096 and the upper limit for this relationship is 0.036. Both these values are according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H7 has the t value of 6.13, which means the p value for this relationship is > 0.001. These values do not support H7. TMC do not plays a mediating role between DL and BDAC's as DL and TMC has a negative effect on BDAC's altogether. It means that the leaders should not rely on human or senior management of the firm instead leaders should formulate a strategy or process through which the desired outcome becomes achievable.

H13 has the mediating effect of IIOT on the relationship between DL and BDAC having a β value of 0 representing H13. β value reflect the effect size from one variable to another. 0 means that an increase of one unit in DL and IIOT will not result as a increase or decrease of BDAC. SD for this relationship is 0.001. A standard deviation of 0.001 suggests that the individual values in the dataset are very close to the mean. The dataset related to this relationship is highly concentrated around the mean, indicating low variability. It indicates a higher level of confidence in the precision of the data.

Whereas, confidence interval having lower limit value for this relationship is -0.002 and the upper limit for this relationship is 0.001. Both these values are not according to the set parameter because, there should be no zero between the lower limit value and the upper limit value.

T value should be greater than 1.96 and if the T value is > than 1.96 it means the p value < 0.005 and if T value is > than 2.58 it means the p value is < 0.001.

H7 has the t value of 0.08, which means the p value for this relationship is < 0.005. These values do not support H7 because DL and IIOT do not effect BDAC's altogether. IIOT do not mediates the relationship between DL and BDAC's which was initially proposed. It may be because it is employee who uses this technology and may be the employee are not aware that how to utilize this technology in its full capacity.

In conclusion, DL do not effect BDAC's directly. DL need to work on process or means through which DL can achieve their desired outcomes. DL should formulate a DSP through its digitalized vision. DL should utilize his/her collaborative approach to strengthened DDC for enhancing BDAC's. DL should focuse towards employee's relationship with other industrial managers. DL should use his/her digital skills to promote employee social capital through digital platform which may play an effecting role in getting access to updated information and knowledge sharing which is essential for BDAC's. Other than this DL should also work for the DLIT of employee. The more the employees are digitally literate the more effective BDAC's organization would have which will ultimately influence DDDM positively.

Table.9 Mediation testing

| H | Relationship | β | SD | T Value | LL (2.5%) | UL (97.5%) | Result |
|---|---|---|---|---|---|---|---|
| H3 | DL -> DSP -> BDAC | 0.056 | 0.011 | 4.99 | 0.033 | 0.077 | Accepted |
| H5 | DL -> DDC -> BDAC | 0.022 | 0.008 | 2.83 | 0.005 | 0.036 | Accepted |
| H9 | DL -> DSC -> BDAC | 0.376 | 0.027 | 14.20 | 0.323 | 0.428 | Accepted |
| H7 | DL -> TMC -> BDAC | -0.072 | 0.012 | 6.17 | -0.096 | -0.05 | Rejected |
| H11 | DL -> DLIT -> BDAC | 0.222 | 0.017 | 13.11 | 0.189 | 0.255 | Accepted |
| H13 | DL -> IIOT -> BDAC | 0 | 0.001 | 0.08 | -0.002 | 0.001 | Rejected |

*(Source: Author's own)*

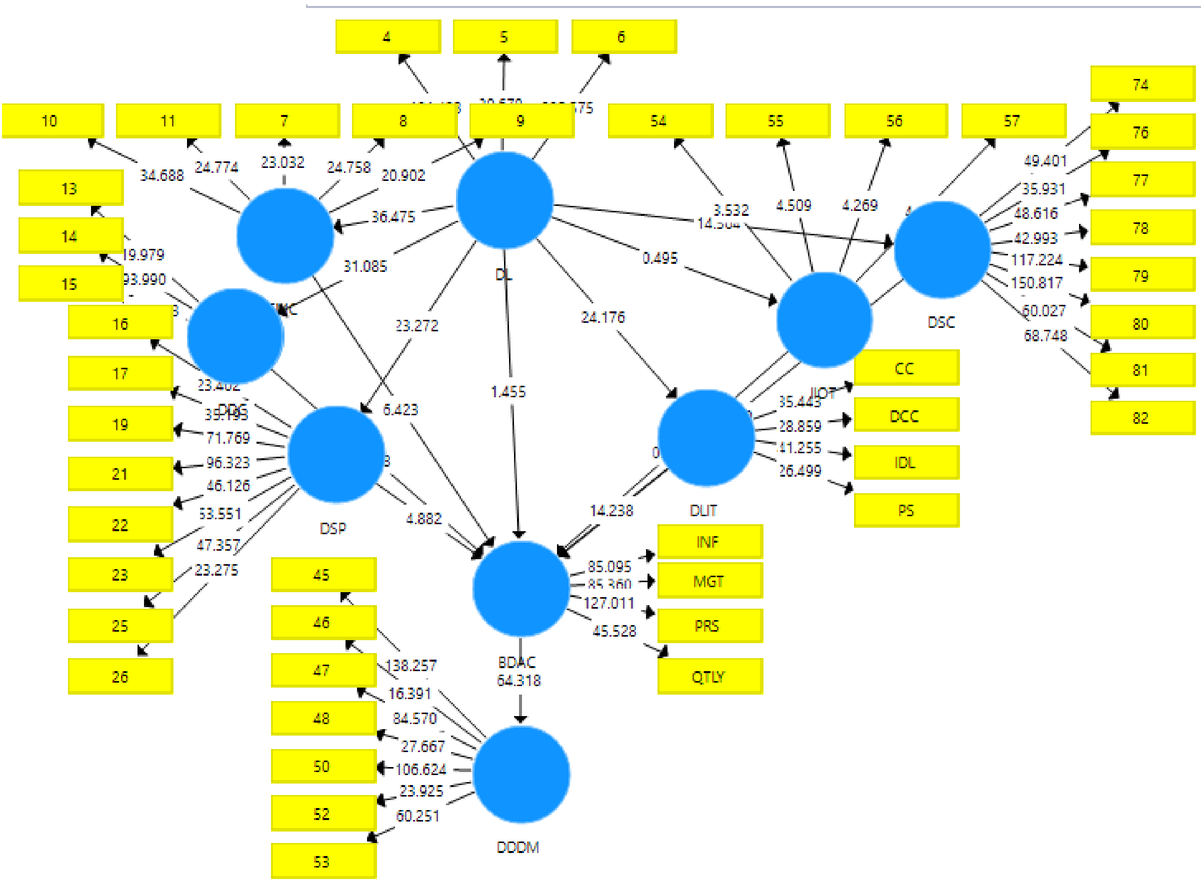


*Fig 5 Bootstrapping with indicators (Source: Author's own)*

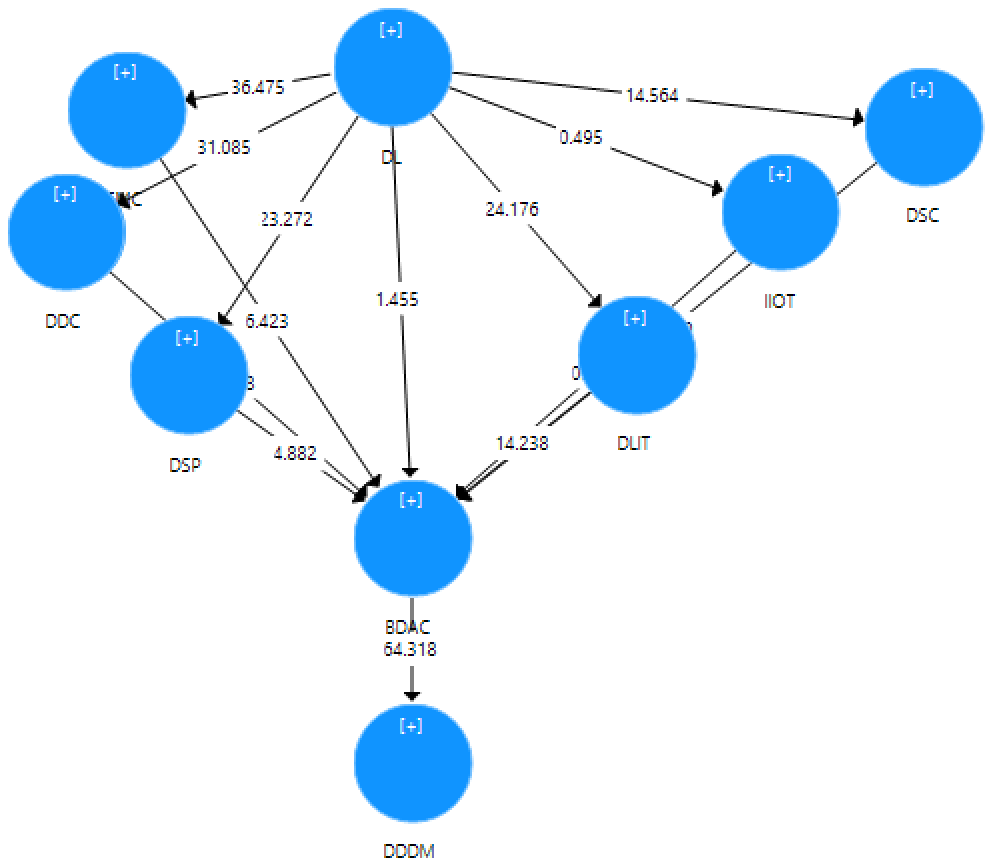


*Fig 6 Bootstrapping without indicators (Source: Author's own)*

# 6. DISCUSION

Study was initiated with a research problem that senior industry managers are confused that how to initiate strategic digital transformation initiatives in their firm (Ghosh et al., 2021). Followed by the aim that is to provide a framework for organizational, human, and technological capabilities enhancement to boost BDAC's for DDDM. These research problem and aim generates a relevant research question that how DL will enhance organizational capabilities, human capabilities and technological capabilities to influence DDDM through BDAC.

Organizational capabilities that include DSP, DDC and TMC are positively link with DL. DL has a positive influence on DSP, DDC and TMC, DL will play its role during digital transformation for enhancing DSP, DDC and TMC. DL has the strongest effect on TMC followed by the DDC and DSP with a β value of 0.751, 0.691 and 0.669 respectively.  This is how DL will enhance organizational factors including DSP, DDC and TMC.

Human capabilities including DSC and DLIT is also influenced by DL. DL will play its role during digital transformation for enhancing DSC and DLIT. DL is positively associated with DSC and DLIT. DL have the strong effect on DLIT which is 0.701 followed by DSC which is 0.563. This is how DL enhance human factors including DSC and DLIT for digital transformation.

Technological factor including IIOT which was also proposed that DL will influence IIOT unfortunately hypothesis was rejected because DL has no significant impact on IIOT. The effect size of DL on IIOT is 0.043.

Result regarding organizational and human capabilities were according to expectation but the results regarding technological enhancement is not according to expectation but we are unable to compare these results with previous results as the current study is discussing these relationship for the first time.

It was also proposed that DL will enhance BDAC but the result reveals that DL is not significantly associated with BDAC.

All these six factors categorized in three category includes organizational capabilities having DSL, DDC and TMC, human capabilities including DSC and DLIT whereas technological capabilities having IIOT have the mediating proposed role in the model between DL and BDAC. In this mediating role some of the variables are as per expectation but some of them did not meet the proposed hypothesis.

Organizational capability including DSP and DDC mediates the relationship between DL and BDAC. The confidence interval is also up to the acceptable level. Whereas TMC which was also supposed to mediate the relationship between DL and BDAC fails to mediate the relationship. TMC as mediation has the negative impact on the relationship between DL and BDAC. Furthermore, the confidence interval value is also not according to the required range.

Human capabilities including DSC and DLIT mediates the relationship between DL and BDAC having a significant result. The confidence interval is also up to the acceptable level.

Technological capabilities including IIOT was also supposed to mediate the relationship between DL and BDAC but the results shows that the IIOT did not mediates the relationship between DL and BDAC. The effect size of IIOT as mediator on the relationship between DL and BDAC is zero and is not significant which means we cannot implement these results on whole population. The confidence interval is also not according to the desired values.

Last, the impact of BDAC on DDDM was also proposed and it is found after data analysis that BDAC has a positive effect on DDDM. The effect size of BDAC on DDDM is 0.882, which is the highest effect size in the whole model. T value and the values for the confidence interval are all with in the desired range.

# 7. CONTRIBUTION

The main purpose of scientific research in management sciences is the upgradation of theoretical and practical knowledge in the relevant field. Current study has some theoretical and practical contribution, which is discuss below in the relevant sections.

## 7.1 Theoretical contribution

This study makes noteworthy contributions to the existing literature in several ways. Firstly, it adds to the discourse on DL, a field that is still in its emerging stages. We have established that DL enhance organizational capabilities, such as DSP for big data value creation, fostering DDC, and enhancing TMC. DL also enhance human capabilities, such as DSC and DLIT. Secondly, we have also determined that the relationship between DL and BDA capability relies on the enhancement of organizational and human capabilities. We posit that effective leadership positively influences operational capabilities when supported by strategic-level competencies, including strategic planning and DDC. In the context of DDDM and DCs, we argue that to develop relevant DCs at the operational level, organizations need to enhance DCs at the strategic level. Thirdly, we contend that DL is also crucial for DDDM, as DL enhance BDACs through the enhancement of organizational and human capabilities. DDDM relies on BDACs, achievable through DL and the enhancement of organizational and human capabilities. Additionally, Lee et al. (2023) suggest that information system scholars should shift their focus to organizational capabilities rather than IT expenditures.

This study makes a substantial contribution to the conceptualization of BDACs. Prior investigations, exemplified by Wamba et al. (2017), have approached the study of BDA through a tripartite framework, encompassing personal, infrastructure, and managerial dimensions. In contrast, the present study enriches the BDAC construct by introducing big data quality as an integral dimension. The authors advocate that aspects of big data quality, including meticulous data cleaning and the elimination of extraneous data to ensure accuracy and completeness, should be orchestrated by the analytical team tasked with data analysis. This proposition is predicated on the notion that the analytical team possesses a nuanced understanding of the objectives and scope of the data analytics endeavor, thereby enabling judicious data handling. Moreover, the implementation of data quality practices within the analytical department facilitates the pursuit of additional information or insights pertinent to the data, a practice underscored as pivotal by Janssen et al. (2017).

## 7.2 Practical contribution

DSP is a crucial aspect for a DL to effectively navigate the complexities of the digital landscape. By engaging in DSP, DL can align their organization's goals with digital initiatives, ensuring a cohesive and forward-thinking approach towards boosting BDAC’s. This process involves analyzing current digital capabilities, identifying areas for improvement, setting clear objectives, and developing a roadmap for implementation.

Furthermore, DDC plays a key role in the success of digital initiatives. By fostering collaboration among different departments within an organization through digital platform, DL can leverage diverse expertise and perspectives to drive BDAC. Collaboration between departments such as IT, marketing, sales, and operations can lead to more holistic digital strategies and solutions that address the needs of the entire organization.

In a study by McKinsey & Company (2018), it was found that organizations that excel in digital strategy and collaboration across departments are more likely to outperform their competitors in terms of revenue growth and profitability. This highlights the importance of DSP and DDC in achieving digital success.

DL plays a crucial role in leveraging BDAC’s within organizations. To enhance these capabilities, it is essential for DL to rely on DSC and DLIT. DSC refers to the relationships, networks, and connections that individuals or organizations have in the digital realm. It encompasses the ability to leverage these connections for knowledge sharing, collaboration, and problem-solving.

By tapping into DSC, DL can access a wealth of information and expertise from their networks, enabling them to make decisions that are more informed when it comes to BDA.

Furthermore, DLIT is another critical component for enhancing BDAC’s. DLIT refers to the ability to effectively navigate, evaluate, and utilize digital technologies and tools. In the context of BDA, DL enables DL to understand the complexities of data collection, processing, analysis, and interpretation.

In conclusion, DL that relies on DSC and DLIT is well-positioned to enhance BDAC's within organizations. By leveraging DSC for knowledge sharing and collaboration, and by developing strong DLIT skills for effective data utilization, DL can drive improve decision-making and achieve competitive advantage in today's data-driven business environment.

# 8. CONCLUSION

Study has been conducted for survival of those firms that are not in category of future ready organization. Study has proposed a model through which, organizations would be converted into smart factories for their survival. Data has been collected from 227 top managers of firms in Pakistan. Structure equation modelling is applied with bootstrapping for mediation test, results shows that organizational capabilities and human capabilities is crucial for achieving BDAC and DDDM.

All the organizational factors including DDC, DSP and TMC is positively influenced by DL, which confirms the capability of DL to set a proper DSP, it digital skills for transforming department collaboration into digital collaboration. Furthermore, DL also enhances the TMC that is crucial for implementing technologies such as BDA and DDDM. DDC and DSP also mediates the relationship between DL and BDAC positively. Whereas, TMC did not mediates the relationship between DL and BDAC.

Human factor including DSC and DLIT are positively influence by DL that further mediate the relationship between DL and BDAC positively.

Technological factor comprises of IIOT is neither influence by DL nor it mediate the relationship between DL and BDAC.

Current study shows an holistic view of the capabilities organization posses through which organizations can achieve their desired outcome that is BDAC's for DDDM in current study context. Study also provides an empirical evidence that how the sub capabilities of digital transforming capability of dynamic capability view plays their role in enhancing the BDAC's for DDDM.

Without addressing these organization and human factors BDAC and DDDM will not be achieve and implementation of big data solutions in its true sense will remains a dream.

# 9. LIMITATION

Study has chosen snowball sampling, a non-probability sampling method, that is commonly used in research to reach populations that are difficult to access through traditional random sampling techniques. While snowball sampling has its advantages in reaching hidden or hard-to-reach populations, it also comes with limitations that researchers need to consider. One major limitation of snowball sampling is the potential for sampling bias (Faugier & Sargeant, 1997). This bias can arise due to the non-random nature of the method, as participants are recruited based on existing connections and referrals, leading to a sample that may not be representative of the entire population (Magnani et al., 2005). Snowball sampling is particularly prone to selection bias, where participants who share similar characteristics or views are more likely to be included in the study (Lalla et al., 2020).

Moreover, snowball sampling may restrict the diversity of the sample and limit the range of perspectives represented in the research (Nuseeb et al., 2021). As the sampling method relies on referrals from initial participants, there is a risk of homogeneity in the sample, with new participants being more likely to resemble the individuals who referred them (Flanagan & Lewis, 2019). This can lead to a lack of variability in the data collected and may compromise the generalizability of the findings (Møller et al., 2021).

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# LIST OF PUBLICATIONS BY THE AUTHOR

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Web of Science Researcher ID:

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## Journal publication

1. Shariq, S. M., Mukhtar, U., & Anwar, S. (2018). Mediating and moderating impact of goal orientation and emotional intelligence on the relationship of knowledge-oriented leadership and knowledge sharing. Journal of Knowledge Management. https://doi.org/10.1108/JKM-01-2018-0033. (WOS Q1).
2. Shamim, S., Yang, Y., Zia, N. U., Khan, Z., & Shariq, S. M. (2023). Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy. Journal of Business Research, 167, 114168. https://doi.org/10.1016/j.jbusres.2023.114168. (WOS Q1).
3. Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2018). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. Information & Management https://doi.org/10.1016/j.im.2018.12.003. (WOS Q1).
4. Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. Technological Forecasting and Social Change, 168, 120766. https://doi.org/10.1016/j.techfore.2021.120766. (WOS Q1).
5. Shamim, S., Zeng, J., Choksy, U. S., & Shariq, S. M. (2020). Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. International Business Review, 29(6), 101604. https://doi.org/10.1016/j.ibusrev.2019.101604 (WOS Q1).
6. Shariq, S. M., Chromjakova, F., & Ortega, M. J. R. (2023). The importance of accountability for knowledge sharing: The role of knowledge-oriented leadership. International Journal of Organizational Leadership, 12(4), 369-388. https://doi.org/10.33844/ijol.2023.60383.

## Submitted for Journal Publication

1. Shariq, S. M., Chromjakova, F., Shamim, S., Maria J. (2024) Enhancing the data-driven decision-making and big data analytics capability through digital leadership and organizational capability optimization. British Journal of Management.

## Conference proceedings

1. Shariq, Syed. Rajnoha, Rastislav. (2022). Achieving big data decision-making quality through digital leadership and knowledge sharing at transfer point in big data chain. DOKBAT 2022 - 18th International Bata Conference for Ph.D. Students and Young Researchers (Vol. 18). Zlín: Tomas Bata University in Zlín, Faculty of Management and Economics. Retrieved from http://hdl.handle.net/10563/52379
2. Shariq, S., Chromjaková, F., & Mohamed, K. A. A. (2022). Achieving Data Driven Decision-Making Quality Through Digital Leadership and Organizational Optimization. Proceedings of the First Australian International Conference on Industrial Engineering and Operations Management, Sydney, Australia.
3. Haider, Ismat. Dohnalova, Zuzana. Shariq, Syed. (2022) A literature review on changing consumer food choices during the covid- 19 pandemic. In DOKBAT 2022 - 18th International Bata Conference for Ph.D. Students and Young Researchers (Vol. 18). Zlín: Tomas Bata University in Zlín, Faculty of Management and Economics. Retrieved from http://dokbat.utb.cz/conferenceproceedings.
4. Shariq, S. M., & Chromjaková, F. Role of Digital Leadership in Achieving Digital Readiness Through Organizational Optimization. Proceedings of the 6th European Conference on Industrial Engineering and Operations Management Lisbon, Portugal, July 18-20, 2023

## Verified Peer reviews for Journals

Web of Science Researcher ID: AAH-6710-2020

| | |
|---|---|
| Journal of Knowledge Management (Q1, WOS) | 3 Papers |
| Journal of Business Research (Q1, WOS) | 1 Paper |
| Business Process Management Journals (Q3) | 1 Paper |

# PROFESSIONAL CURRICULUM VITAE

# Syed Muhammad Shariq

## Verified Peer reviews for Journals

Web of Science Researcher ID: AAH-6710-2020

| | |
|---|---|
| Journal of Knowledge Management (Q1, WOS) | 3 Papers |
| Journal of Business Research (Q1, WOS) | 1 Paper |
| Business Process Management Journals (Q3) | 1 Paper |

## Funding Acquired

Funding Program: Internal Grant Agency

Funding Institution: Tomas Bata University in Zlin

1. Process optimization and knowledge information support in Industry 4.0 companies. IGA/FaME/2020/009 (Principal investigator 2021).
2. INDUSTRY 4.0 – development of big data driven business concepts oriented on lean management transfer (governance role and SMEs implementations model). IGA/FaME/2021/006. (Team member 2021-2022).
3. Research and implementation of big databased intelligence solutions for transformation of traditional firm into digitalize one. IGA/FaME/2022/008. (Principal investigator 2022-2023).

## TEACHING ASSISTANCE

Seminar 1: The impact of modern technologies on human resource management for the course named human resource management 1.
Seminar 2: Business Intelligence seminar for the course named basics of information system.

**Supply Chain Officer**

***Buxly Paints Limited* [10/2017 – 10/2020]**

Country: Pakistan

◦ *Material Planning*

◦ *Forecasting production demand*

◦ *Stock Management*

◦ *Inventory maters at plant*

◦ *Problem solving*

◦ *Controlling loss during production*

◦ *Owning and executing production plan*

◦ *Provide dispatch planning to distribution department*

◦ *Push sales team for achieving national targets*

**Modern trade manager**

***Gujranwala Food Industries (Pvt) Limited (JOJO) (Confectionery)*** **[02/03/2015 – 01/08/2016]**

Country: Pakistan

◦ *Production*

◦ *Dispatching*

◦ *Ensure availability at customer shelf*

◦ *Invoices follow up for cash collection*

◦ *Ledger reconciliation*

◦ *Distribution maters like documentations, payments, stock level, stock audit, primary & secondary sales were under my doma*in.

## DIGITAL SKILLS

Oracle Financials / SAP Business One / Smart PLS / IBM SPSS / Python for intermediate level

## EDUCATION

**Ph.D. candidate**

*Tomas Bata University in Zlin* [09/2020 – Current]

Address: (Czech Republic)

**M.Phil. Management Science**

*GIFT University* [2017 – 2019]

Address: (Pakistan)

**MSc, Accounting & Finance**

*GIFT University* [2012 – 2014]

Address: (Pakistan)

**Bachelor of commerce**

*University of the Punjab* [2009 – 2011]

Address: (Pakistan)

# 11. APPENDICES

**Appendices 1**

| Definitions | Theory used | Context |
|---|---|---|
| BDAC is defined as "… a firm's ability to assemble, integrate, and deploy its big data-specific resources." | Resource-based view, IT capability | |
| The conceptualization of BDAC contains three dimensions (i.e., management, technology, and human) that "… highlight[s] the importance of the complementarities between them for high level operational efficiency and effectiveness for improved performance and sustained competitive advantage." | Entanglement view of socio-materialism, resource-based view, IT capability | |
| BDAC is defined as "the ability to acquire, store, process and analyze large amount of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion | Information lifecycle management view | Health Care |
| BDAC is regarded as "… the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force." | Resource-based view, IT capability, entanglement view | |
| "…organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyse data, thereby producing insights that enable | Organizational information processing theory | Supply chain management |

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| data-driven operational planning, decision-making, and execution.” | | |
| BDAC in the supply chain context is referred to as “the ability of organizations to collect and organize supply chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise or real-time or near real-time and visualize it intuitively to create proactive supply chain system and support decision making.” | | Supply Chain management |
| BDAC is broadly defined “as the ability of a firm to provide insights using data management, infrastructure, and talent to transform business into a competitive force.” | Resource-based view, ***dynamic capabilities view*** | |
| “BDAC is an organizational facility with tools, techniques, and processes that enable the organization to process, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision making and execution.” | ***Dynamic capabilities view,*** contingency theory | Supply Chain management |
| “Big Data Capability as a firm's capability of identifying sources, where large volumes of various kinds of data flow out at high speed, and collecting, storing, and analyzing such Big Data for the purpose of accomplishing the firm's strategic as well as operational goals.” | ***Dynamic capabilities view*** | |

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| BDA capability refers to a company's management ability, that is, the continuous use and deployment of big data resources with the strategic goal of creating value and developing a competitive advantage for the firm.” | Resource-based view, ***dynamic capabilities view*** | |
| BDA capabilities are conceptualized as “a third-order formative construct of BDA management capability, BDA personnel expertise capability and BDA infrastructure flexibility capability” (p. 298). “BDA management capabilities comprise of essential first-order capabilities of planning, investment decision making, coordination and control. | Resource-based view, ***dynamic capabilities view*** | Supply Chain management |
| BDAC is “defined as the ability of a firm to capture and analyse data towards the generation of insights by effectively orchestrating and deploying its data, technology and talent.” | Resource-based view, ***dynamic capabilities view*** | |
| “Organizational BDA capabilities are an ensemble of capabilities that include infrastructure flexibility, management capabilities and personnel capabilities. | ***Dynamic capabilities view*** | |
| Big data analytics capability is defined as the ability to acquire, store, process and analyse large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover | Configuration theory | Health care |

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| business values and insights in a timely fashion." | | |
| BDA capability is defined as the ability of the organizations in developing competency to generate business insights based on organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (e.g., analytics skill or knowledge) capabilities for increased business performance" | Resource-based view, ***dynamic capabilities view*** | Manufacturing Firm |
| BDACs refer to "the extent to which BDA has been used to provide business insights into primary activities (e.g., production, distribution, and customer service). | Resource-based view, ***dynamic capabilities view***, knowledge management | |
| BDAC is "the ability of a firm to capture and analyze data toward the generation of insights by effectively orchestrating and deploying its data, technology, and talent." | Resource-based view, information governance theory | |
| BDAC is defined as "the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight." | Resource-based view, ***dynamic capabilities view***, IT capability | |
| "Big data analytics capabilities refer to the firm's ability to recognize and analyze different data sources to provide valuable insights." | Knowledge based ***dynamic capabilities view***, social capital theory Information processing theory | Supply Chain management |
| BDAC is referred to as "a holistic approach of analysing and processing big data for value creation." | Resource-based view, ***dynamic capabilities view***, socio-materialism theory | |
| BDAC is defined "as the capability of firms to combine, | IT capability, resource-based view | |

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| integrate, and deploy specific big data resources." | | |
| "*BDAC is broadly defined as the competence to provide business insights using data management, infrastructure (technology), and talent (personal)capabilities to transform the business into a competitive force.*" | ***Dynamic capabilities view*** | |
| BDAC is defined as "a firm's ability to assemble, integrate, and deploy its big data-specific resource." | Resource-based view, ***dynamic capabilities view*** | |
| *BDAC refers to the ability to provide business insights in the big data environment by using big data analytics personnel, big data analytics technical, and big data analytics management capabilities*. | ***Dynamic capabilities view*** | Service sector |
| BDACs are referred to "*as a balanced combination of requisite human resource, big-data skills, advanced technologies supported by large datasets to generate analytical reports and actionable insights utilized, produced, and processed by mathematical, statistical techniques, and machine learning tools for enhanced performance*. | Resource-based view, ***dynamic capabilities view*** | |
| BDAC refers to "*a firm's ability to assemble, integrate, and deploy its big data-specific resources* | Source-position-performance theoretical framework | Sustainability development projects |
| *BDAC is termed as an organization's capacity to efficiently and strategically* | Resource-based view, organizational information processing theory | Higher education institutions |

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| *arrange, assemble, and apply BDA resources so that effective decision-making can be made to enhance overall organization's Performance* | | |
| BDACs refer to a "*holistic process that involves the collection, analysis, use and interpretation of data for various functional divisions to gain actionable insights, create business value and establish competitive advantage* | Resource-based view, ***dynamic capabilities view***, institution-based view | Manufacturing sector |
| BDAC is defined "*as the ability to acquire, store, process, and analyze large amounts of data in various forms and deliver meaningful information to users, allowing them to discover business values and insights in a timely fashion.* | Resource-based view | |
| BDAC "*refer to the company's abilities to leverage on technology and talent to exploit BD towards the generation of the insights that are necessary to overperform rivals.* | Knowledge-based view, IT capability | |
| BDAC is recognized as "*the competence to provide business insights using the capacity of data management, infrastructure (technology) and talent (personnel) to transform a business into a competitive force.* | Process-oriented ***dynamic capabilities***, business value | |
| BDAC in supply chain management is described as "*the ability of organizations to collect and organize supply* | Resource-based view, ***dynamic capabilities view***, contingency theory | Supply chain management |

| | | |
|---|---|---|
| *chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise, or real-time, or near real-time, and visualize it intuitively to create proactive supply chain system and support decision making,*" | | |
| *BDAC is defined as the ability of a firm to capture and analyze data for the generation of insights by effectively orchestrating and deploying its data, technology, and talent* | Resource-based view, ***dynamic capabilities view*** | |
| BDAC is defined "*as a firm's ability to assemble, integrate and deploy its big data-based resources.* | Organizational information processing theory | |
| BDA capability refers to "*an enterprise's ability to realize data-driven operation plan and decision-making through processing, organizing and analyzing data.* | Organizational information processing theory | Supply chain management |
| *BDA capabilities comprise a firm's techniques, processes and talents that enable the organization to process, visualize and analyze big data, thereby producing insights that enable data-driven operational planning, decision-making and execution* | | |
| BDAC is defined as "*the combined ability to store, process, and analyze large amounts of data to provide meaningful information to users.* | Organization development theory | |

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| BDAC is defined as an "*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyse data thereby producing insights that enable data-driven operational planning, decision-making, and execution.* | Organizational information processing theory | Supply chain management |
| BDAC refers to "*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyse data, thereby producing insights that enable data-driven operational planning, decision-making, and execution* | Organizational information processing theory | Health care |
| BDAC is defined as "*the ability to acquire, store, process, and analyse large amount of health data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion* | Resource orchestration theory | Health care |
| BDACs are proposed with three dimensions of tangible resources, human resources and intangible resources, which are analyzed "*from three dimensions of management capabilities, infrastructure capabilities and human capabilities* | Resource-based view, IT capabilities | Smart cities, public sectors |
| "*Big data analytics capabilities (BDAC) are broadly defined as the competence to provide* | Organizational information processing theory, institutional theory | Micro, small and medium enterprises |

| | | |
|---|---|---|
| *business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force* | | |
| "*BDAC are defined as the knowledge, skills, and abilities that combine technology and management issues to explore data potential through sophisticated statistical, computational, and visualization tools.* | Resource-based view, ***dynamic capability view***, and absorptive capacity view | |
| *BDAC refers to an organizational ability that enable firms to capture, consolidate, and analyze data thus generating new insights to implement data-driven programming, decision-making, and operation*. | Organizational information processing theories | Supply chain management |
| "*BDACs are an organizational ability with the necessary tools and techniques to process big data to produce internal associations, patterns, and insights.* | | |
| *The term big data analytics capability is the extent wherein firm has distinctive capability to identify quality problems, competency to set optimal pricing, trace profitable customers and manage lowest inventory using big data tools*. | | |
| *Big data analytics capabilities refer to obtaining knowledge from internal or external partners and* | Knowledge-based ***dynamic capability view*** | |

| | | |
|---|---|---|
| *gaining market insight through big data tools* | | |
| "*BDA capability refers to a company's management ability, that is, the ongoing deployment of big data resources at the strategic aims to create value and develop a competitive advantage for the firm.* | | |
| *…the ability of an organization to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments* | ***Dynamic capabilities view*** | Supply chain management |
| *BDAC is defined as the ability of a firm to capture and analyze big data toward the generation of insights by effectively orchestrating and deploying its data, technology and talent.* | Knowledge-based view | |
| *the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight.* | Knowledge-based view and contingency theory | |
| *a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions to gain actionable insights, create business value, and establish competitive advantage* | Resource-based view, ***dynamic capability view*** | Supply chain management |
| "*a holistic process that involves the collection, analysis, use, and interpretation of data for various* | Resource-based view, ***dynamic capability view*** | Supply chain management |

| | | |
|---|---|---|
| *functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage.*” | | |
| *BDAC is defined as the ability to develop business insight by using data management, technical foundations and talents.* | | |
| “*it can be defined as the organization's capacity to provide insight into the use of data management, infrastructure and human capabilities to increase the competitiveness of the business* | Resource-based view, process-oriented ***dynamic capability view***, socio-materiality theory | |
| *the ability of an organization to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments.* | | Supply chain management |

*(Source: Huynh 2023)*

**Appendices 2**

## Proportion of theories used in existing literature

| # | Row Labels | Sum of Count | % |
|---|---|---|---|
| 1 | absorptive capacity view | 1 | 1% |
| 2 | business value | 1 | 1% |
| 3 | Configuration theory | 4 | 4% |
| ***4*** | ***Dynamic capabilities view*** | ***22*** | ***25%*** |
| 5 | entanglement view | 2 | 2% |
| 6 | information governance theory | 1 | 1% |
| 7 | Information lifecycle management view | 1 | 1% |
| 8 | Information processing theory | 1 | 1% |
| 9 | institutional theory | 1 | 1% |
| 10 | institution-based view | 1 | 1% |
| ***11*** | ***IT capabilities*** | ***6*** | ***7%*** |
| ***12*** | ***IT capability*** | ***1*** | ***1%*** |
| ***13*** | ***knowledge management*** | ***1*** | ***1%*** |
| ***14*** | ***Knowledge-based dynamic capability view*** | ***2*** | ***2%*** |
| ***15*** | ***Knowledge-based view*** | ***3*** | ***3%*** |
| 16 | Organization development theory | 1 | 1% |
| 17 | Organizational information processing theories | 8 | 9% |
| ***18*** | ***process-oriented dynamic capability view,*** | ***2*** | ***2%*** |
| 19 | Resource orchestration theory | 1 | 1% |
| ***20*** | ***Resource-based view*** | ***25*** | ***28%*** |
| 21 | social capital theory | 1 | 1% |
| 22 | socio-materialism theory | 2 | 2% |
| 23 | Source-position-performance theoretical framework | 1 | 1% |
| | Grand Total | 89 | 100% |

*(Source: Huynh 2023)*

**Appendices 3**

# Statistical method used in existing literature

| Methods | No. of studies | % |
|---|---|---|
| ***PLS-SEM*** | ***47*** | ***51%*** |
| Covariance-based SEM | 19 | 21% |
| OLS and probit regression | 10 | 11% |
| Hierarchical regression | 7 | 8% |
| Mediation analysis | 4 | 4% |
| Fuzzy-set QCA | 2 | 2% |
| Others | 3 | 3% |
| Total | 92 | 100% |

*(Source: Huynh 2023)*

**Appendices 4**

## Questionnaire

I am a doctoral student at Tomas Bata University in Zlin, Czech Republic and collecting data for which you are requested to fill this questionnaire. I assure you that provided data will be used for educational purpose only. Thank you in anticipation. Answer question according to mentioned scale-

1 = Strongly disagree; 2 = Disagree; 3 = Moderately disagree; 4 = Neutral; 5 = Moderately agree; 6 = Agree; 7 = Strongly agree

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | Our leadership think that using digital tools is fun. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 2 | Our leadership is a digital expert. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3 | When it comes to digital knowledge, our leadership is always up to date. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4 | Our leadership is driving the digital transformation forward proactively in our unit. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 5 | Our leadership can make others enthusiastic about the digital transformation. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 6 | Our leadership has a clear idea of the structures and processes that are needed for the digital transformation. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 7 | Our organization's top management expresses how big data partnering will provide significant business benefits to the firm. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 8 | Our organization's top management expresses how big data partnering will create a significant competitive arena. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 9 | Our organization's top management articulates collaborative vision for big data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 10 | Our organization's top management stablishes the metrics to monitor big data utlization success through partnering. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
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| 11 | Our organization's top management formulates big data related strategies for organizational information sharing. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 12 | In our organization, business analysts and line people meet regularly using digital platform to discuss important issues related to big data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 13 | In our organization, business analysts and line people from various departments regularly attend cross-functional meetings using digital platform to discuss important issues related to big data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 14 | In our organization, business analysts and line people coordinate their big data related efforts harmoniously through digital platform. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 15 | In our organization, information is widely shared between business analysts and line people using digital platform so that those who make decisions or perform jobs have access to all available know-how related to big data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 16 | Our organization have broad, long-range big data related goals known to all managers (GOALS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 17 | Our organization have specific, short-term big data related goals known to all managers (GOALS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 18 | Our firm's big data related actions are based more on formal plans than on intuition (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 19 | Our organization have a department devoted exclusively to big data related planning (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 20 | Our organization hold regular managers' meetings to discuss big data related strategy (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 21 | Our organization use mathematical and computer models as big data related planning aids (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 22 | Our organization have a written big data related plan for the next 12 months (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 23 | Our organization's big data related planning outlook is more long-term than short-ter (ANALYS). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 24 | Our organization search systematically for information about our competitors (SCANING). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 25 | Our organization use special market research studies (SCANING). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 26 | Our organization search systematically for new products(SCANNG). | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 27 | Our organization continuously examine innovative opportunities for the strategic use of big data analytics. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 28 | Our organization enforce plans for the introduction and of big data analytics adequately. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 29 | Our organization enforce plans for the utilization of big data analytics adequately. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 30 | Our organization perform big data analytics planning processes in systematic ways. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 31 | Our organization perform big data analytics planning processes in formalized ways. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 32 | Our organization frequently adjust big data analytics plans to better adapt to changing conditions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 33 | When our organization make big data analytics investment decisions, it consider and project about how much these options will help end-users make quicker decisions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 34 | In our organization, business analysts and line people frequently meet to discuss important issues formally. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 35 | In our organization, business analysts and line people frequently meet to discuss important issues informally. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 36 | The data our organization use, reflect high level of accuracy. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 37 | Our organization donot face problems in decision-making due to accuracy of data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 38 | In our organization new data replace the old data in timely manner. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 39 | Data is regularly updated according to changes happening in business environment. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 40 | We often face problems in decision-making due to incomplete data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 41 | Our data donot contains a lot of irrelevant details. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 42 | Our data is formated in a precise manner for decision-makers. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 43 | Our data reflect high level of relevance with our business operations. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 44 | Our data are useful for our business decision-making. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 45 | We believe that our organization make good decisions based on the data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 46 | The data based decisions which our organization make result in the desired outcomes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 47 | Our organization is satisfied with the outcomes of its data based decisions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 48 | Our organization's decisions based on the data improve organisational performance. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 49 | Our organization's decisions based on the data do not improve organisational performance.* | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 50 | Our organization's data based decision-making cost is very low. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 51 | Our organization spend a lot of time in making decisions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 52 | Our organization don't need a lot of people to make decisions based on the data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 53 | Our organization make timely decisions based on the data. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 54 | In my opinion, IIoT technology will be applied mainly for business to business markets instead of business to consumer markets. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 55 | In my opinion, IIoT technology will be used mainly to offer services instead of products | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 56 | In my opinion, the data gained from IIoT will be used to create additional value for revenue generation in the future | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 57 | In my opinion, the partner structure of IIoT product's business models is more complex than the partner structure of business models of conventional products | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 58 | I am confident in browsing, serching, filtering data, and information & digital content. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 59 | I regularly use cloud information storage services or external hard drives. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 60 | I verify the source of information I find. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 61 | I actively use a wide rang of online communication tools at work. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 62 | I choose digital tools and technologies for collaborative processes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 63 | I have net-etiquette (differentiate behavioural norms) while using CT and interacting in digital environments. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 64 | I can produce complex digital content in different formats. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 65 | I can apply advanced formatting functions of different tools to the content I or others have produced. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 66 | I respect copyright and license rules and I know how to apply them to digital information and content. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 67 | I am able to apply advanced settings to some software and programs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 68 | I periodically check my privacy settings and update my security programs on the devices that I use to access the internet | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 69 | I am able t select safe and suitable digital media, which are efficient and cost-effective in comparison with others. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 70 | I am abe to solve a technical problem or decide what to do when technology does not work. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 71 | I can use digital technologies to solve problems. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 72 | I am able to use varied media to express myself creatively. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 73 | In general, we have a very good relationship with other departments using new digital platforms. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 74 | Our relationship departments uses digital technologies to know what knowledge we have at our disposal | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 75 | We know that what knowledge could be relevant to which department through digital technologies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 76 | We feel connected to our business partners through digital technologies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 77 | We know our business partners will always try and help us out through digital technologies if we get into difficulties | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 78 | We can trust our business partners to lend us a hand through digital technologies if we need it | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 79 | We can rely on our business partners when we need support in our work based on digital technologies. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 80 | Our business partners and we always agree on what is important at work | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 81 | Our business partners and we always share the same ambitions and vision related to digitalization at work. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 82 | Our business partners and we are always enthusiastic about pursing the collective goals and missions related to digitalization of the whole organization. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Syed Muhammad Shariq

# Role of digital leadership, digital technologies and dynamic capabilities to influence big data analytical capabilities for data driven decision-making

Role digitálního vedení, digitálních technologií a dynamických schopností při ovlivňování analytických schopností velkých dat pro rozhodování založené na datech

Doctoral Thesis

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