From Big Data Analytics to Organizational Agility The Role of Entrepreneurial Orientation: A Study of Manufacturing Firms

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ABSTRACT

In the age of digitalization, big data analytics capabilities have emerged as one of the most critical organizational resources. Many organizations make considerable investments in these resources with an intention to improve their agility. However, the mechanism to reap agility from big data analytics still requires extensive empirical research and analysis. This study extends the prior models of big data analytics by examining the mediating effects of entrepreneurial orientation in the relationship between big data analytics capability and organizational agility. Using Partial Least Squares-Structured Equation Modelling (PLS-SEM), the responses collected from 104 firms in Jordan were modelled and analyzed. Results demonstrate that entrepreneurial orientation explains the relationship between big data analytics capabilities and agility. This finding contributes to the management literature by demonstrating how big data analytics capabilities may enhance firm entrepreneurial orientation. Rather than conceptualizing the entrepreneurial orientation of the firm as a static characteristic, we argue that the big data analytic capabilities play a key role in developing organizational agility through its role in improving entrepreneurial orientation, which subsequently creates value for firms, their customers and the other stakeholders.

Keywords: Organizational agility, Big data analytics capabilities, Entrepreneurial orientation, PLS-SEM.

ÖZ

Dijital dönüşüm çağında büyük veri analiz yetkinliği kurumsal kaynaklarımızın en önemlisi konumuna gelmiştir. Birçok kurum çevikliklerini geliştirmek amacı ile veri kaynaklarına yatırım yapmaktadır. Ancak büyük veri analizinden kurum çevikliğine giden yolu etkileyen mekanizmaların doğru anlaşılması için daha fazla görgül araştırmaya ihtiyaç vardır. Bu çalışmada büyük veri analizi ile kurumsal çeviklik ilişkisine girişimcilik yöneliminin aracı rolü eklenerek büyük veri analizi modeline bir katkı yapılmaktadır. Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi (PLS SEM/Partial Least Squares Structural Equation Modelling) kullanılarak Ürdün'den 103 firmadan toplan veriler analiz edilmiştir. Sonuçlar girişimcilik yöneliminin büyük veri analizi ile kurumsal çeviklik ilişkisini açıkladığını göstermiştir. Bu sonuç büyük veri analizi yetkinliğinin girişimcilik yönelimini de geliştirebileceğine işaret etmesi ile yönetim literatürüne önemli bir katkı yapmaktadır. Çalışmada yenilikçi bir yaklaşım olarak firmaların girişimcilik yönelimi değişmez bir özellik olarak değil de veri analizi yetkinliklerince gelişebilecek bir özellik olarak ele alınmaktadır ve girişimcilik yetkinliği daha yüksek olan kurumların krumsal çevikliğinin arttığı ortaya konulmaktadır. Kurumsal çeviklik sayesinde kurumların müşterileri ve tüm paydaşları için yarattığı değer artmaktadır.

Anahtar Kelimeler: Kurumsal çeviklik, Büyük veri analizi yetkinliği, Girişimcilik yönelimi, PLS-SEM.

DEDICATION

This work is dedicated to my wonderful family

My

(father, mother, brother, sister, wife, son, daughter),

for their endless love, pray, support, and encouragement.

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First of all, I thank the Almighty God for giving me a strength to complete this unpretentious work.

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LIST OF ABBREVIATIONS

AM	Agile Manufacturing
BD	Big Data
BDA	Big Data Analytics
BDAC	Big Data Analytics Capabilities
BDAI	Big Data Analytics Infrastructure
CMV	Common Method Variance
DC	Dynamic Capability
DCT	Dynamic Capability Theory
DDC	Data-Driven Culture
EO	Entrepreneurial Orientation
GDP	Gross Domestic Product
GLA	Greater London Authority
INO	Innovativeness
IOT	Internet of Things
IT	Information Technology
JD	Jordanian Dinar
KBV	Knowledge-based View
MB	Megabyte
MCA	Market Capitalizing Agility
MGS	Management Skills
NPD	New Product Development
OA	Organizational Agility
OAA	Operational Adjustment Agility

OL	Organizational Learning
PLS-SEM	Partial Least Square – Structural Equation Modelling
PROA	Pro-activeness
RBV	Resource-Based Review
RFID	Radio-frequency identification
RISK	Risk-taking
TS	Technical Skills
VIF	Variance Inflation Factor

Chapter 1

INTRODUCTION

1.1 Introduction to the Background of the Study

This chapter deliberates the background to the study in which the fundamental notion is discussed. The main matter to be researched is elucidated to delineate the research problem, thus, instituting the research objectives. The discussion in this chapter is being formulated to view the researched topic in a holistic view, then drilling it down to a given point.

To couple the declarative and procedural knowledge of this study, this chapter provides the background to the study, purpose of the study, main contribution of the study, states the research questions and the research hypotheses to be tested, the importance of the current study, assumptions, limitations, and the key term definitions.

1.2 Background of the Study

The growth in digital transformation in various aspects of life has led to increased interest from both researchers and practitioners to consider the factors that sustain this growth. One of the digital transformation technologies that changed the conventional shape of doing business in the 21st century is the use of “Big Data” (BD) (Mcafee & Brynjolfsson, 2012).

Big data refers to a huge amount of heterogeneous data that can be curated and analyzed using a large variety of platforms (e.g. Apache Hadoop, Apache Spark, Microsoft Azure, and Tableau Software), these data are characterized by high volume, high variety, and high velocity, which traditional data systems and approaches to data management are unable to capture, organize, and analyze (H. Chen et al., 2012; Zeng & Khan, 2019). Organizations need to have analytical capabilities to properly use big data (Gandomi & Haider, 2015) in order to build products faster (Aydiner et al., 2019; Choi et al., 2018), and offer new economic commodities to meet customer's changing demands (Ghasemaghaei & Calic, 2019; Opresnik & Taisch, 2015). Thus, big data are closely associated with firm performance because it enables agility. Organizations that use big data analytics have the ability to quickly sense, think, and act to capture opportunities in a volatile market. Likewise, data analytics in the big data revolution have induced a more entrepreneurial attitude and inspired many data entrepreneurs, resulting in considerable changes in the entrepreneurship concept among organizations (Sedkaoui, 2018). In addition to big data, the entrepreneurial orientation of a firm is considered another factor that is believed to influence firm performance in today's competitive and volatile environment. A firm that is innovates, and can anticipate change and is prepared to alter their prior activities, and is willing to take risks is said to have a higher level of entrepreneurial orientation compared to firms where strategic orientation is more aligned with protecting their current position (G.T. Lumpkin & Dess, 1996; Rosenbusch et al., 2013; J. Wiklund, 1999). Entrepreneurially oriented firms are more likely to be in a position to utilize their big data analytic capabilities to create value (Covin & Lumpkin, 2011) and similarly their big data analytics capabilities can enable them to develop a more entrepreneurial orientation.

Hence, Entrepreneurial orientations explains the performance implications of big data analytics. Darwis (2017) stated that a critical characteristic that builds internal and external capabilities as well as integrate and reconfigure these capabilities is entrepreneurial orientation which results in the ability to respond to aggressive and hyper-volatile market conditions is entrepreneurial orientation. Thus, entrepreneurial orientation establishes the ground and paves the way for higher levels of agility (Christopher, 2000; Gölgeci et al., 2019).

While agility has been considered an antecedent of business value and a major enabler of a business's performance (Côrte-Real et al., 2017; Overby et al., 2006), the IT capability literature have not investigated how agility can be enhanced (Oh & Pinsonneault, 2007) and only emphasized performance of the firm (Ferraris et al., 2019; Mikalef et al., 2020; Rialti et al., 2019; Wamba et al., 2017). Although small number of studies (Ghasemaghaei et al., 2017; Hyun et al., 2020) have addressed the conditions (i.e. organizational culture, fit perspectives) under which big data can lead to agility by investigating possible moderators, our understanding of the mediator that enable big data to enhance agility is still unclear. Thus, to help us understand the mechanism that makes this relationship possible our research model seeks to investigate the role of entrepreneurial orientation as a possible mediator that facilitates the big data analytics capabilities - organizational agility relationship.

Perpetuating BDA capability is essential because firms must be able to reconfigure their existing business model or build a new one in response to currently changing business conditions (Ashrafi et al., 2019). Accordingly, this study uses a hybrid conceptual framework based on the Resource-Based View (RBV) and the Dynamic Capability Theory (DCT) to elaborate on how big data capability enable business deliverables (agility) that can fundamentally enhance firm's competitive position.

1.3 Purpose of the Study

This dissertation aims to provide knowledge on the relationship between Big Data Analytics Capabilities and Organizational Agility and the role of Entrepreneurial Orientation. More precisely, identifying how Big Data Analytics Capabilities together with Entrepreneurial Orientation may improve Organizational Agility in manufacturing industries. Also, assessing the utilization of Big Data Analytics, Entrepreneurial Orientation and Organization Agility in Jordanian manufacturing sector.

1.4 Main Contribution

The manufacturing industry is a critical economic driver for Jordan. It has Direct contribution to GDP of 24%, and indirect contribution to GDP of 40%, employs 254,000 people which is a contribution to the national workforce of 21%, there are some 18,000 industrial facilities and its contribution to exports is 93%. Thus, the efficiency and effectiveness of the manufacturing industry is critical for the Jordanian society. The current study will help to guide policy makers and practitioners in adoption of Big Data Analytics in order to have a more resilient and agile industry.

1.5 Research Questions

(1) How do big data analytics capabilities (BDAC) impact organizational agility (OA)?

(2) What role does entrepreneurial orientation play in the big data analytics capabilities - organizational agility relationship?

1.6 Research Hypotheses

***Hypothesis* 1:** Big data analytics capabilities have a positive and direct relationship with organizational agility.

***Hypothesis 2*:** Big data analytics capabilities have a positive relationship with entrepreneurial orientation.

***Hypothesis* 3:** Entrepreneurial orientation is positively associated with organizational agility.

***Hypothesis* 4:** Entrepreneurial orientation mediates the relationship between big data analytics capabilities and organizational agility.

1.7 Significance of the Study

The significance of this study can be discussed from a theoretical, practical, and scientific perspective.

Theoretical significance, the importance of this facet comes from addressing one of the IT-related trends (Big data analytics) as a competitive strategy in the current digital global marketplace. On the other hand, this study has drawn up the way for other scholars and researchers to deeply investigate on the area and contributing to the body of relevant knowledge.

Practical significance is represented by focusing on the dimensions of big data analytics capability, entrepreneurial orientation, and organizational agility in manufacturing companies working across the Hashemite kingdom of Jordan. Moreover, providing new insights to practitioners and decision makers to come up with an appropriate mechanism to overcome big data and agility challenges. This to a large extent, will have a positive impact on the industrial sector contribution to GDP.

Scientific significance is manifested by what will this study introduce to illustrate the hypotheses that have been explored, and check their validity alongside with contradictory facts to build new proved scientific knowledge, perspectives and skills.

1.8 Assumptions

Several assumptions that the researcher adopted during this experimental study. First of all, we assume that respondents willingly responded in an honest manner to questions in the measurement tool. Furthermore, the researcher assumes that the Arabic version of the measurement items were understood in the same context of the original English version and be applicable to use in Jordan. In regard to sampling units, we assume that our sample of participants is representative of the manufacturing sector in Jordan and that those interested to participate and those that did not fill out the questionnaire do not form noticeable groups. Therefore, the findings of this study can be built on as all scientific necessary procedures were followed accordingly during the entire study stages.

1.9 Limitations

In reality, conducting any research study is accompanied with several limitations; These limitations in one way or another hamper partly or whole process of the study, or may have a hurtful effect on the generalizability of the research findings. In this part we summarized the limitations of this study into four main categories as the following:

(1) *Spatial Limit*: the current study has addressed the manufacturing firms listed on the Jordan chamber of industry and working across Jordan; (2) *Human Limit*: we targeted the top management positions only in participating facilities; (3) *Timeframe Limit*: the researcher managed this study of the period between December, 2020 and June, 2021; (4) *Practical Limits*: we have investigated the relationship between the capability of big data analytics and organizational agility based on the model which is developed for the purpose of this study. These limits are not considered weaknesses in the true sense, but rather avenues for future research.

1.10 Definition of Key Terms

Big data analytics capabilities (BDAC) in this study is composed of the following latent variables: data-driven culture (DDC), organizational learning (OL), technical skills (TS), management skills (MGS), and big data analytics infrastructure (BDAI). Similarly, Organizational agility (OA) consists of operational adjustment agility (OAA) and market capitalizing agility (MCA). Likewise, entrepreneurial orientation (EO) consists of innovativeness (INO), pro-activeness (PROA), and risk-taking (RISK). The origin and definitions of the constructs are provided in Table 1.1.

Table 1.1: Constructs and Definitions

Construct	Sub-Construct	Definition	Reference(s)
Big Data Analytics Capabilities		A firm's ability to collect, analyze, and use of huge number of heterogeneous datasets to create superior value and establishing competitive advantage.	Belhadi et al. (2020); Mikalef et al. (2020); Wamba et al. (2020); Rialti et al. (2019).
	Data-driven culture	The behavior of decision-making based on insights extracted from data analysis results.	Duan et al. (2020); Lunde et al. (2019); Carillo et al. (2019).
	Organizational learning	The process of extending and disseminating the knowledge to those who need it to improve performance levels.	Mikalef et al. (2017); Dezi et al. (2018); Oh (S.-Y. Oh, 2019); Ipek (İpek, 2019).
	Technical skills	The competence to use new technological tools or algorithms to draw readable information from large dataset.	Ferraris (2019); Mikalef et al. (2020); Dubey et al. (2019).
	Management skills	Practice of planning, implementation and evaluation of data-related process and resources, and understanding how the output extracted from big data can be applied to different functional areas in the organization.	Lozada et al. (2019); Akter (2016); Gupta and George (2016).
	BDA infrastructure	Availability of the BDA ingredients such as applications, hardware, data, and networks to enable the BDA team to quickly response to changes in system components of a firm.	Belhadi et al. (2020); Shokouhyar et al. (2020); Wamba et al. (2017); Akter et al. (2016).
Entrepreneurial Orientation		The Processing, practicing, and decision-making actions that lead to exploit opportunities in the current and/or new market.	Lumpkin and Dess (1996); Covin and Slevin (1991); Miller (1983).
	Innovation	Firm's ability to find an unconventional solution for problems and creating substantial changes in their capabilities to attain competitive advantage.	Niemand et al. (2020); Sedkaoui (2018); Lumpkin and Dess (1996).
	Risk-taking	The firm's willingness to take bold actions to invest in opportunities available in the business environment.	Gnizy (2019); Tahmasebifard et al. (2017); Lumpkin and Dess (1996).

Construct	Sub-Construct	Definition	Reference(s)
	Pro-activeness	Firm's conduct toward expecting future needs of markets and the changes in the business environment before competitors.	Gölgeci et al. (2019); Lumpkin and Dess (1996).
Organizational Agility		Capability to swiftly sense, think, and act to seize market opportunities in an environment which is unpredictable and rapidly changing.	Hyun et al. (2020); Ashrafi et al. (2019); Mandal (2019); Ghasemaghaei et al. (2017).
	Operational adjustment agility	The firm's internal and external business operation ability to rapidly identify market demands and turn it into competitive action.	Zaini et al. (2020); Li et al. (2020); Queiroz et al. (2018); Ghasemaghaei et al. (2017).
	Market capitalizing agility	The ability to quickly respond to the target market's need by constant monitoring of the available opportunities and rapidly developing products and/or services to satisfy customer desires.	Li et al. (2020); Cheng et al. (2020); Ghasemaghaei et al. (2017).

Note: All definitions at the organizational level.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of previous research on the relationship between big data analytics, entrepreneurial orientation, and organizational agility. It introduces the framework for the study that involves the key purpose of the research described in this dissertation. Two main things that are literature review and hypotheses development will be discussed. First, the literature that support theories and different concepts regarding with big data, entrepreneurship, and agility in the context of manufacturing industry. In details, dynamic capability theory; big data analytics issues (characteristics, applications, benefits, challenges); entrepreneurial orientation aspects (dimensions, the connection to big data and manufacturing flexibility); the sides of organizational agility such as categories and framework. Next, how the researcher develops the hypotheses of this study in hand.

2.2 Underpinning Theory

- *Dynamic capability theory (DCT)*

The competitive advantages that organizations strive to obtain and sustain are a result of their abilities to cope with volatile markets and their changing business environment in an effective and rapid way. Dynamic capability theory can be used to explain how these abilities enable competitiveness.

The dynamic capabilities theory recognizes the importance of having certain types of resources and is based on the resource based model (Teece et al., 1997). These resources are made up of tangible and intangible assets. While the capital, technology, facilities, equipment (Itami & Roehl, 1991) are classified as tangible, the knowledge, innovativeness, corporate culture, and firm reputation (Khan et al., 2019) can be classified as intangible. If firm resources that are valuable, rare, costly to imitate and not easy to be substituted can be organized to capture value, this will enable a firm to gain sustainable competitive advantage and outstanding performance (Yadav et al., 2017). While the resource-based view may be seen as static, the dynamic capabilities on the other hand refers to the competence of a firm to adapt and change their resources internally and externally in response to or in anticipation of and possibly to have an impact on their business environment (Teece, 2012). Dynamic capability (DC) operates through three main mechanisms: sensing capacity, seizing capacity, transforming capacity (Teece, 2009). Sensing capacity is essentially about identifying and exploring market demands and technological opportunities, both inside and outside of the organization (Hodgkinson & Healey, 2011; Teece, 2014). Seizing capacity refers to mobilization and coordination of resources to fulfil identified customer needs, market opportunities and threats as quickly as necessary (Teece, 2007). Transforming capacity focuses on resource renewal, knowledge generation and integration, organizational structure (Katkalo et al., 2010; Moliterno & Wiersema, 2007; Teece, 2007). In short, business value creation (organizational agility, sustainable competitive advantage) does not come from the allocation of resources but their orchestration and optimum use.

2.3 Big Data Analytics Capability

Big data analytics is regarded as a revolutionary term that have great impact on managing innovation, productivity, as well as competition (Manyika et al., 2011; Mcafee & Brynjolfsson, 2012). Chen et al.(2012) used the term “big data analytics” as a component of business intelligence that is concerned with data mining, data infrastructure, data visualization and analysis. The last 10 years has seen an exponential increase in interest in the big data field from scholars and practitioners to understand the business value the firms can create through big data analytics (Rathore et al., 2021; Sivarajah et al., 2017).

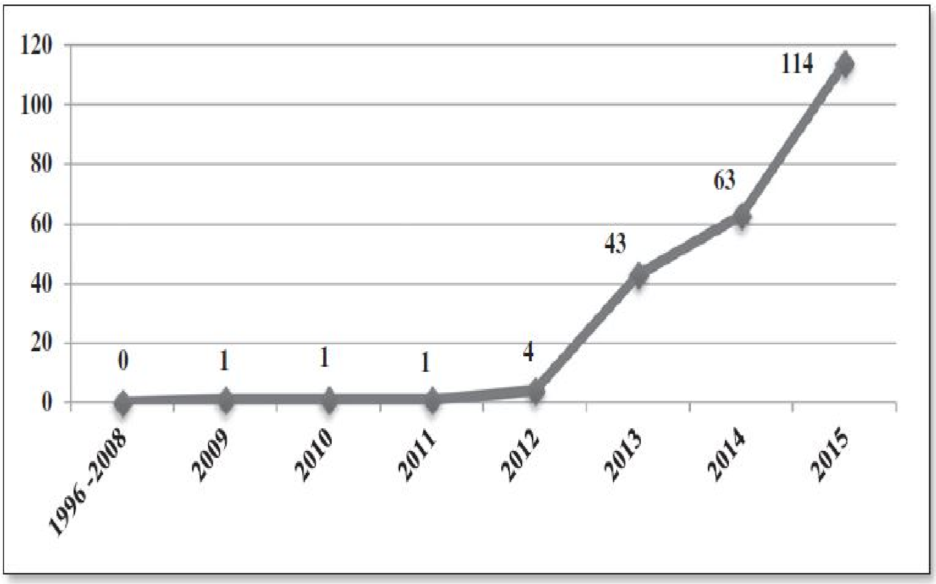

Figure 2.1: Total Number of Papers Published Between 1996- 2015
Source: Sivarajah et al. (2017)

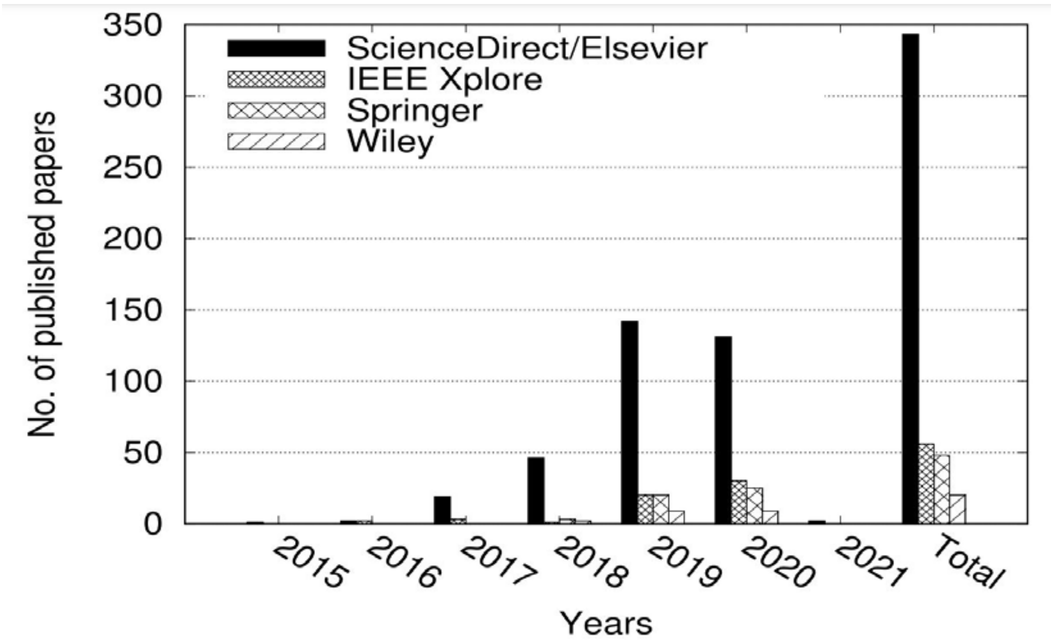

Figure 2.2: Number of Journal Papers Published by Different libraries
Source: Rathore et al. (2021)

Understanding the effects of big data analytics requires that we consider three important points. First, data is an asset. Big data should be considered as an information resource that may be utilized more than one time to find solutions to many problems (Erevelles et al., 2016). Second, firms need to have routines, processes, and capabilities to interpret big data. To generate intelligence and gain insights from big data, organizations need to be able to have developed mechanisms to manage it (Côrte-Real et al., 2017). Third, firms have to be able to manage and utilize the knowledge that emanate from these data. A vast amount of knowledge will be generated as a result of the analysis; however, the knowledge will be useful only if the firm can use it properly and create value from the knowledge (Ferraris et al., 2019). In the light of these three points, dynamic capabilities theory is a lens to perceive the effects of big data analytics. In the rapidly changing environment, a firm's competitive advantage is directly related to their dynamic capabilities according to Teece et al. (1997).

In the same connection, Wamba et al. (2017) have noticed that organizational and financial performance within an organization are one of the process-oriented dynamic capabilities consequences. Accordingly, big data analytics which provide the access to the necessary information can be seen as the lower-order capabilities which enable higher-order capabilities such as organizational agility providing direct competitive advantage for the firm (Chen et al., 2015; Liu et al., 2013). Big data analytics capabilities (BDAC) can help a firm to process large volume, wide-variety, and high-velocity data in order to create veracious and valuable business insights for establishing competitive advantages (Fosso Wamba et al., 2015; Gunasekaran et al., 2017). Similarly, only through big data analytics platforms firms can integrate and analyze structured, semi-structured, and unstructured data for well-defined and timely business decisions (Cao et al., 2019; Puklavec et al., 2018; Rouhani et al., 2016; Shollo & Galliers, 2016). Liu et al. (2014) reported that adopting big data analytics in decision-making have potential to decrease the cost of customer acquisition by 47 percent and revenues growth by 8 percent. They report that more than 300 billion dollars in health services every year, if big data analytics outcomes were used creatively by the U.S. health care system. In the U.K. government researchers expect that the value of digital transformation technologies, in particular, big data analytics combined with the internet of things could make up 2.7 percent of the GDP which would mean more than 300 billion pounds-sterling (Côrte-real et al., 2020). Big data enabled fraud detection and tax collection systems could generate more than 100 billion euro for European governments (McGuire et al., 2012). Another example, General Electric (GE) relies on big data in its design of energy systems to improve their operational efficiency (Wamba et al., 2017).

Furthermore, eBay and Amazon use customer browsing data and many retailers use loyalty-card data to increase their sales through improving the forecast of customer-buying trends (Chen et al., 2012; Gandomi & Haider, 2015). Therefore, it is important to study the impact of BDAC on different types of organizational agility to attain competitive advantage.

2.3.1 Big Data Characteristics

Compared to conventional data used in relational database systems, big data have different characteristics called "V's" (volume, velocity, variety, veracity, value) defined by National Institute of Standards and Technology (NIST) in 2015 (Kostakis & Kargas, 2021). Consequently, it requires specialized technological capabilities and tools to control the flow of external and internal information on the business model, for transforming them into strategic insights which are imperative to introduce new products or services to meet customer's and stakeholder's needs, increasingly informed (Morabito, 2014; Surbakti et al., 2020). Liu et al. (2020) and Zhang et al. (2018) summarized five big data characteristics as shown in Figure 2.1.

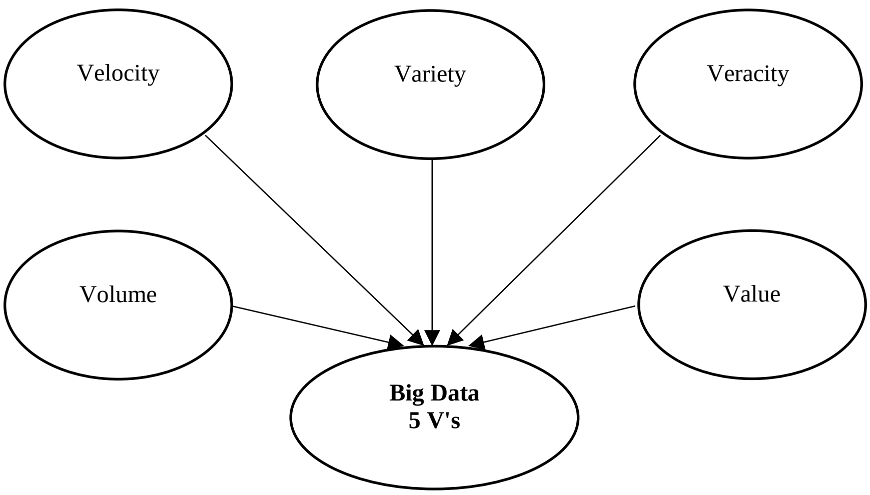

Figure 2.3: Big Data Characteristics
Source: designed by the researcher

Volume: focuses on data size that reach the level of Petabyte (10^9 MB) or even Exabyte (10^{12} MB). For example, approximately 1.7 Megabytes per second were generated by human in 2020 (Azeem et al., 2022). Walmart rolls up 2.5 petabytes of data per hour from over a million customers (Marr, 2017).

Velocity: the second characteristic refers to the speed of data creation, processing and use. High velocity, plays important role in the implementation of big data technologies and coping with their main associated challenges (Silva et al., 2021). Amazon's pricing system has been able to monitor competitor's pricing and send alerts every 15 seconds, resulting in personalized suggestions to customers (Kopp, 2013).

Variety: represents the different types of data collected from various channels in the big data ecosystem. Big data fuel comes from data that may be structured (such as demographic data, SQL databases, spreadsheets) or semi-structured (such as e-mail communications, web page content, CSV files with data in various formats) and unstructured (such as voice, video, or data collected by automatic sensors) which constitute 80 percent of the data in companies (S. Chen et al., 2020). For example, Netflix analyses more than one billion sentiments such as loved and hated reviews on of movies to understand and predict follower's tastes (Davenport et al., 2007).

Veracity: this attribute of big data relates to the extent of data reliability and trust. Data need a legal power of information source to ensure its truthfulness, legitimacy, and safety. A greater level of veracity allows companies to focus on data that is truthful, pertinent, and timely to extract business gains (Erevelles et al., 2016).

Twitter records data from over 300 million users to fitter determine which tweet directions to offer on follower's timelines (Marr, 2020).

Value: refers to the benefits derived from big data such as strategic, informational, and transactional benefits (Shahriar Akter & Wamba, 2016; Mohamed et al., 2020). For example, Google acquires geospatial data from Android users to improve Google Maps searching engine (Hariri et al., 2019). Facebook monitors users' browsing history to send a tailored advertising.

2.3.2 Applications of Big Data

In the digital transformation rush, the big data investment shall touch 229.4 billion US dollars by 2025 (Deepa et al., 2022). Big data technologies have notable interventions in various areas of industry and business that have capitalized from these technologies. These domains generate a massive amount of data that require big data analytics tools provided by web services platforms or standalone software's for creating efficient and effective insights. In this regard, we will emphasis on five areas, namely (1) healthcare; (2) social interaction; (3) business and economic; (4) environmental management; (5) public sector.

1. Healthcare

Improving health systems are necessary for economic development. The health care industry generates approximately 150 Exabyte in 2011 with an increase rate between 1.2 to 2.4 Exabyte per year (Mohamed et al., 2020). Medical data can be used to make precise and real-time medical decisions by doctors and health-care providers, thereby improving the living standards to the public.

Clinical data come from the electronic medical records which include personal genetics (Nguyen et al., 2017), pharmaceutical data and personal data (e.g. practices, preferences, financial). Integrating and analysing these huge amounts of data attend the increase in population growth is important for diagnosing, prediction, prescription of medical cases. For instance, heart rate, blood pressure, blood glucose levels, and chest breathing data collected from sensors in real time are sent to mobile devices and data center for processing diagnosis, and treatment decisions (Manogaran et al., 2018).

An important role in disease study and care delivery can be given to big data analytics. Recently, these analytics have been utilized to come up with many innovative solutions used in the healthcare practice. One of the most recent applications, Big data and artificial intelligence together have contributed to revealing the secrets of COVID pandemic, for managing it properly (Mehta & Shukla, 2022).

2. Social Interaction

The evolution of big data research has an impact on social interactions, both on individuals and organizations resulted in a new, sophisticated context of social networking concepts (Lytras et al., 2017). More explicitly, it is about investigating the impact of data and their analysing outcomes to the comprehension and addressing of social issues (Lytras & Visvizi, 2020). In the past few years, many social media platforms like Facebook, YouTube, WhatsApp, Instagram, Twitter, and LinkedIn that has used big data technology tools to collect information and disseminate among their users. This information is employed in building user behavior modelling to develop user-centric applications through sensing his navigation patterns (Ajah & Nweke, 2019).

3. Business and Economic

The applications of big data analytics in the commercial sector are assorted and noticeable in a wide range of discipline such as supply chain management, marketing and services management, operation management, and quality control. The firms that use big data analytics are 36 percent more likely to excel their rivals in terms of operating efficiency and revenue growth, as well as 62 percent of retail businesses sense the competitive advantages from information management and analytics (Barlette & Baillette, 2020). Big data analytics findings provide organizations in deep understanding customers' preferences and enabling customization, and optimizing process coordination and supply chains (Ardito et al., 2019; Grover et al., 2018). In particular, General electric (GE) is hiring big data analytics to find out new service models for their industrial lines. On the other hand, The Greater London Authority (GLA) set up the London data store in 2010, for increasing transparency and innovation through developing new customer-facing products and services, and supporting operational service improvements (Wright et al., 2019).

4. Environmental Management

In contemporary business realm, the integration of the sustainable development goals into business models is increasingly attracting the attention of many decision makers worldwide to generate economic, social, and environmental improvements at the individuals and organization level. In view of the environment, Big data are considered suitable and innovative step stone for tackling ecological matters which have a close connection with the sustainable developments of the economy and society (Gohil et al., 2021).

Recent data-related environmental management studies main focus on measuring and enhancing water and energy consumption, emissions reduction, and optimizing waste management, which in turn, directly affect climate change and global warming phenomenon (Beier et al., 2022; Su et al., 2020; Sun & Scanlon, 2019). The Chinese government in August 2015, assessed that big data could be an instrument use to model an effective reaction mechanism for monitoring the ecological environment (GOSC, 2015). In Alicante, Spain, smart water device is used to access to detailed information on household water consumption patterns to come up with recommendations for better water conservation and enhancement of the capacity of water supply system (March et al., 2017). In another example, the Environment Protection Agency of the United States of America (EPA) and Energy Information Administration (EIA) of the same country utilize big data to set up the emissions database, which manages carbon footprint data resulting from power stations in the US (Song et al., 2018).

5. Public Sector

Institutions in the public sector are one of the producers of “Big Open Data” (Janssen & Helbig, 2018) such as public and security records of individuals, financial data, census datasets, transportation and traffic data, and environment dataset. Commonly, a government is responsible in managing and safeguarding these sensitive data to provide services to the community. Increasingly, governments day-to-day activities have become rely on “Big Data” analytics tools, especially machine learning and artificial intelligence, in which, changed the approach of public service delivery (Löfgren & Webster, 2020). Orchestrating “Big Open Data” supports many developments in the public arena; “Smart Cities” is one of the great examples yet. Smart cities harness the data collected from IOT smart sensors to manage and monitor all city's information and activities, for instance, weather information, natural disaster information, traffic information, and energy and waste management (Giest, 2020; Kousiouris et al., 2018; Rathore et al., 2018). Gasc´o-Hernandez (2018) pointed out that smart cities can help improve the local economy and citizen's standard of life. In a word, the public sector increasingly becomes more conscious of the conceivable value to be obtained from large scale data analytics.

2.3.3 Three Big Benefits of Big Data Analytics

Big data analytics is no longer just a tentative tool in today's managerial practices. Many organizations have begun to attain fruitful results with the approach, and are escalating their exertions to embrace more data and models (Davenportis, 2014). Davenport (2014) highlighted three significant benefits of big data analytics. The following sub-headings will summarize these benefits:

2.3.3.1 Faster, Better Decision Making

From the decision maker's viewpoint, the importance of big data resides in its ability to provide knowledge for building a decision tree to prevent undesirable outcomes and reduce the cost of predicted decisions. More obviously, Big data is a main contributor in the phases of a decision-making process (Intelligence, design, choice, implementation) to make more informed decisions based on meaningful inferences from such data (Elgendy & Elragal, 2014). McAfee and Brynjolfsson (2012) found that businesses that are more data-driven decision making characterised themselves with better operational and financial performance. Likewise, using advanced analytics empowers real-time decision-making capabilities that cannot be accessed by traditional data analytics (Jeble et al., 2018).

In a similar manner, Uber uses big data for real time routing information to minimize pick-up times and optimize the passenger experience (Gunawardena & Jayasena, 2020).

2.3.3.2 New Products Development (NPD)

Many organizations leverage the results of investments in big data analytics in the innovation process through drawing up new ideas to formulating new business models and developing new products and services (Marshall et al., 2015). In particular, executives can rely on the analytics to support new product development (NPD) choices to gain sustainable competitive advantages over their competitors (Ghasemaghaei & Calic, 2019; Johnson et al., 2017; M. Mariani & Borghi, 2019; Markham et al., 2015). The literature identified three stages that advent of big data can be utilized to support a company’s NPD, that is, inspiration of ideas; design and engineering; and test and release (Zhan et al., 2018). In respect of ideas, Big data can assist this stage through the collection of external information to give managers promising ideas (Tsai et al., 2013). Engaging customers in design and engineering process can exhibit their creativity and competence by deriving and assessing new product ideas, and constructing and experimenting virtual prototypes of new product features (Chen et al., 2012; L. Zhang et al., 2018). In the test and release stage, big data allows businesses to transfer individuals from different sources into the roles of end users (Mcafee & Brynjolfsson, 2012; Wamba et al., 2015; Wong, 2012). The UK company “SoundOut” analyse the reviews on unreleased music in the UK and US to predict songs that should be supported through production and distribution and songs that should be avoided (M. M. Mariani & Fosso Wamba, 2020).

2.3.3.3 Cost Reduction

In general, the cost reduction concept has a connection to performance indicators. Firms make use of BDA to support a wide range of performance facets by optimizing their cost planning, in terms of waste reduction, defective units, machine efficiency, process downtime (Popovič et al., 2018). Big data technologies like Hadoop and cloud service analytics provide remarkable cost advantages (Balachandran & Prasad, 2017). For instance, cloud computing services has potentialities to increase manufacturing process capacity with low cost (Almeida, 2017). UPS processes on average 39.5 million tracking requests per day for 8.8 million customers around the world. In 2011, UPS cut of 85 million miles off of daily routes by analysing data comes from sensors in over 46,000 shipping trucks, in result, more than 8.4 million gallons of fuel are saved (Davenport T.H., Dyché, 2013).

2.3.4 Key Challenges for Big Data Analytics

Although, the contributions of BDA are generally seen as important and receive a lot of attention, big data analytics have potential implementation challenges if it is not handled in a proper way. The major challenges relate to managerial and cultural dimensions, while the main barrier is the lack of clear mechanism of how to utilize big data analytics to create values (Vassakis et al., 2018). Big data with their characteristics also means different challenges that might affect the adoption of big data (Al-Sai et al., 2019). As reported by Sivarajah et al. (2017), Akerkar (2014), and Katal et al. (2013), the challenges can be divided into three main categories as outlined below:

Data challenges connect to the features of the data itself (e.g. data volume, velocity, variety, veracity, and value); *Process challenges* are associated with “How” questions – how to collect and prepare data, how to model the data, how to visualize, how to analyse, and how to deploy and maintain deliverables; *Management challenges* cover the aspects of governance, ethics, security and privacy.

2.3.5 Big Data in Manufacturing

Big data technology is one of the pillars of the fourth industrial revolution. Information technology has speeded up the integration between manufacturing systems and the data owned by firms (Gao et al., 2020). In smart manufacturing, industrial big data analytics not only foster firms to meticulously recognize the environmental changes but, also enable data-driven decision making to enhance operational efficiency, minimize costs, and optimize the production process (B. Wang et al., 2021). Manufacturing industry depends on a wide spectrum of automation system such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Product Lifecycle Management, Supply Chain Management (SCM), and Programmable logic controllers (PLC) (Azeem et al., 2022). Whereas these systems control the ongoing processes to increase the firm's productivity and efficiency (Bahl & Bagha, 2021). Many companies are actively using automation, which provide information that can be acted on in order to develop competitive advantages over the other market players through establishment of more robust and resilient manufacturing process that are more flexible. The flexibility allows adjustment to the rapidly shifting market trends and conditions. The following points illuminate the most prominent functions of big data in the manufacturing area:

- *Manufacturing Environment Forecasting*

Managers in manufacturing firms are able to foresee the uncertainties involving equipment performance and failure well before it occurs and to take necessary steps proactively to deal with the possible impacts through the use of big data analytics. An ideal manufacturing system can be developed without facing high costs (Azeem et al., 2022).

- *Manufacturing and Product Design*

A key aspect in manufacturing is the design. With big data, the the conventional product design has been abandoned and a move towards smart design processses has been made possible (Da Cunha et al., 2010). With greater amount of consumer data availability, product designers now have tremendous insights into the consumer views and feedback that they can utilize to develop features in the product design. This provides value-added functionality, as well as streamlining the designing process for the product (Kusiak & Salustri, 2007).

- *Smart Planning*

After the designing phase, the production planning becomes the next crucial step. The first step for an effective production plan is the acquisition and analysis of data that has been acquired through orders received from customers, the timely information on the manufacturing process status, and data on the supply chain systems. So, available resources can be assessed through a supply-and-demand matching and scheduling (Cheng et al., 2015). The second step is to determine level of manufacturing resources that will be optimal and the execution procedures that need to be implemented for to match the needs (Tao et al., 2018). In short, Big data analysis enables a more robust production process arrangement and the machining system (Ji & Wang, 2017), thus improved productivity and quality in minimized cost.

- *Quality Control*

A combination of heterogeneous data-driven techniques (e.g. sensors, RFIDs, machine vision) have facilitated smart quality control practices through collecting a huge data of product quality (Li et al., 2015). Big data analytics can aid the all-inclusive monitoring for quality management that provides quick detection of possible quality defects. This in turn allows fast identification of the sources of the quality problems (Köksal et al., 2011). The analysis of the causes along with the "weighted association rule mining" can identify product failures (He et al., 2017). As a result, the emphasis shifts from only identification and removal of failed products, but an assessment of the quality systems to manage the defects and deficiencies.

- *Smart Maintenance*

Data analytics can precisely diagnose and predict machine-related issues like faults and equipment component lifecycle (Tao et al., 2018; Verma et al., 2013); such information allows engineers to take precautionary actions and make informed maintenance decisions. With big data analytics the maintenance paradigm has transformed from a traditional passive form to a smart and cognitive form, thus extending equipment lifetime and minimizing maintenance costs (Zhang et al., 2015).

Here is an example of a giant manufacturer openness to utilize big data analytics to in their production technique. General Electric (GE) is a company that is in the top 50 globally in terms of revenue generation. It has more than 500 Factories overseas, producing products ranging from home appliance to power stations.

In 2015, General Electric developed and introduced its system named "Brilliant Manufacturing Suite" to integrate their product design, manufacturing process, the procurement and supply chain, logistics and distribution (Azeem et al., 2021). The application works on an integrated to analyzing the manufacturing process through tracking to identify gaps that may lead to possible errors and tackle them in a timely manner. As a consequence, GE has announced that their system has been succeeded to increase the productivity of its factory in Vietnam by 5 percent, likewise, improved the on-time delivery by 25 percent in the jet engine factory in Michigan (Azeem et al., 2021).

2.4 Entrepreneurial Orientation

Resources, individually, may not generate value; organizations need strategy, structure, and internal organizational processes to capitalize on the resources (Barney, 1991; Eisenhardt & Martin, 2000). Entrepreneurial orientation (EO) can facilitate the organizational capability that is needed to utilize the resources that big data analytics capability can produce in enhancing competitiveness (Covin & Lumpkin, 2011).

2.4.1 Entrepreneurial Orientation Dimensions

Miller (1983) conceptualized the EO as a multifaceted construct which involves company’s activities relating to innovation, pro-activeness, and risk-taking. Innovation reveals the enthusiasm of the firm for novelty, creativity, and unconventional thinking that has the opportunity to lead to new production processes and methods, and unrivalled products (Lumpkin & Dess, 1996; C. L. Wang, 2008). Whereas pro-activeness is indicative of the firm’s proclivity to exploit current and new opportunities in the business and their emphasis on being first-mover to be at cutting-edge of the industry (Hornsby et al., 1993).

That is, pro-activeness manifests firm's strength to anticipate future market needs and changes before competitors (Lumpkin & Dess, 2001). According to Lumpkin & Dess

(1996), risk-taking reflects the degree of willingness of the top management to commit firm resources to acquire high profit when the decision implies considerable chance of failure.

2.4.2 Entrepreneurial Orientation in the Age of Big Data

Entrepreneurial companies need to understand not only the current business situation, but also to identify the future challenges and occasions and proactively arrange innovative solutions and accept the related risks before it is too late. Big data analytics platforms can enhance the ability of the organization to find these innovative solutions by allowing immediate and convenient access to various business-related information that was not available before the currency of big data technology (Watson IV et al., 2018). When firms have more access to structured and unstructured information, this allows them to find and analyse new patterns and recognize new trends in the marketplace (G. George et al., 2014; Sivarajah et al., 2017). The information is necessary for innovative products and services as well as recognizing and targeting new markets (Mazzei & Noble, 2017). In addition, organizations that possess a data-driven culture can more skilfully explore environmental opportunities and threats and sense alternative solutions (Côrte-Real et al., 2017), which assists in risk taking propensity. Specifically, big data analytics are essential for effective risk management and allow more accurate assessment of the risks involved in a decision (LaValle et al., 2011). Thus, entrepreneurial orientation (EO) act as a nexus between resources and competitiveness.

2.4.3 Entrepreneurial Practices and Manufacturing Flexibility

In the time of globalization and technological development, entrepreneurial orientation (EO) comes to be needed to improve a firm’s competitiveness and performance. Schumpeter and Backhaus (2003) indicated that the traits of entrepreneurship can be a main source of evolving manufacturing flexibility. In general, a high tendency toward an entrepreneurial attitude in decision making consolidates a firm's tolerance to market trends fluctuation (Covin & Slevin, 1991; Mondal & Espana, 2006). Chang et al. (2007) provided empirical evidence that entrepreneurial practices can enhance manufacturing flexibility in the matter of new products, product mix, and volume. More exactly, innovativeness, risk-taking, and proactiveness can vitalize a firm's dynamic capability to invent new products, expand the range of product lines, and adjust production levels as market needed. Innovativeness engages a firm in creativity and scientific research that may enable the development of products, process, and technological progresses in novel forms (Frese et al., 2002; G. T. Lumpkin & Dess, 1996). As well, Suarez et al. (1996) found manufacturing innovation technologies and production processes can have shorter lead times and allows manufacturing flexibility especially when they are integrated.. With respect to risk-taking, the literature pointed out that it can improve flexibility in manufacturing companies. Nohria and Gulati (1997) and Lumpkin and Dess (1996) state that entrepreneurs who are willing to take risks are would be expected to invest in and use first-time products and engineering technologies. This would allow the firm to seek, develop and exploit new manufacturing solutions and end products in appropriate time to satisfy customers the changing demand. The third dimension of entrepreneurship is proactiveness. Many scholars claim that production flexibility increases when firms act proactively.

Tannous (1996) asserts that firms that have the capability of planning and investment forward develop their capacity to their output levels in line with market fluctuations and shifts. Moreover, there is evidence that that being more proactive may facilitate a firm to benefit from first-mover advantages (Chang et al., 2003).

In sum, manufacturing flexibility cannot be accomplished by merely using automated systems. Rather, manufacturing flexibility entails to be integrated with the firm's entrepreneurial practices.

2.5 Organizational Agility

Increasing number of studies discuss the organizational agility concept (Ghasemaghaei et al., 2017; Hyun et al., 2020; Rafi et al., 2021; Sambamurthy et al., 2003; Zhen et al., 2021). A firm’s capability to face changes and exploit opportunities in hypercompetitive markets is referred to as its agility (Haeckel, 1999). Organizational agility is composed of two main components: Operational Adjustment Agility and Market Capitalizing Agility (Li et al., 2020). These components or dimensions tackle both internal environment concept such as core competencies, talent, and competitive advantage and external environment such as technological forces, customers’ needs, and market opportunities (Aburub, 2015). Ravichandran (2018) advocated that firms should be agile and have tools to sense market orientations and act rapidly to improve their operational activities. Firms can become more agile by enhancing its dynamic capabilities through effective management of acquired knowledge (Overby et al., 2006). In turbulent business environments, organizations encounter unpredicted, unusual, and challenging market conditions; firms need to reconfigure their agile behaviour to maintain their status quo as a cost-effective solution (Sen et al., 2018).

Many researchers discussed the relationship between IT-related capabilities (e.g. big data analytics) and firm agility (Dutta et al., 2014; Işık et al., 2013; Lowry & Wilson, 2016; Tallon et al., 2019; Tallon & Pinsonneault, 2011) to understand the working mechanism of this relation and to harness generated business values in developing the firm's competitive advantage. IT capability increasingly becomes fundamental in configuring competence that defines agility within a firm (Lowry & Wilson, 2016). Particularly, organizations can finetune their processes to not only detect the changes in the marketplace but also present their innovative products and services to their consumers (Queiroz et al., 2018). To summarize, IT-related capability is a key factor to organizational agility, both paving the way toward sustainable competitive advantage.

2.5.1 Categories of Organizational Agility

A clear agility conceptual framework can work for essential underpinning for the further development of organizational agility studies (P. M. Podsakoff et al., 2016), therefore a successful implementation in practice. Zhang and Sharifi (2000) and Walter (2021) developed a conceptual model to demonstrate and aid in understanding the notions of agility in the manufacturing firms. The model explores three interrelated principal disciplines: agility drivers, agility enablers, and agility capabilities. Figure 2.2. Illustrates the conceptual map of organizational agility.

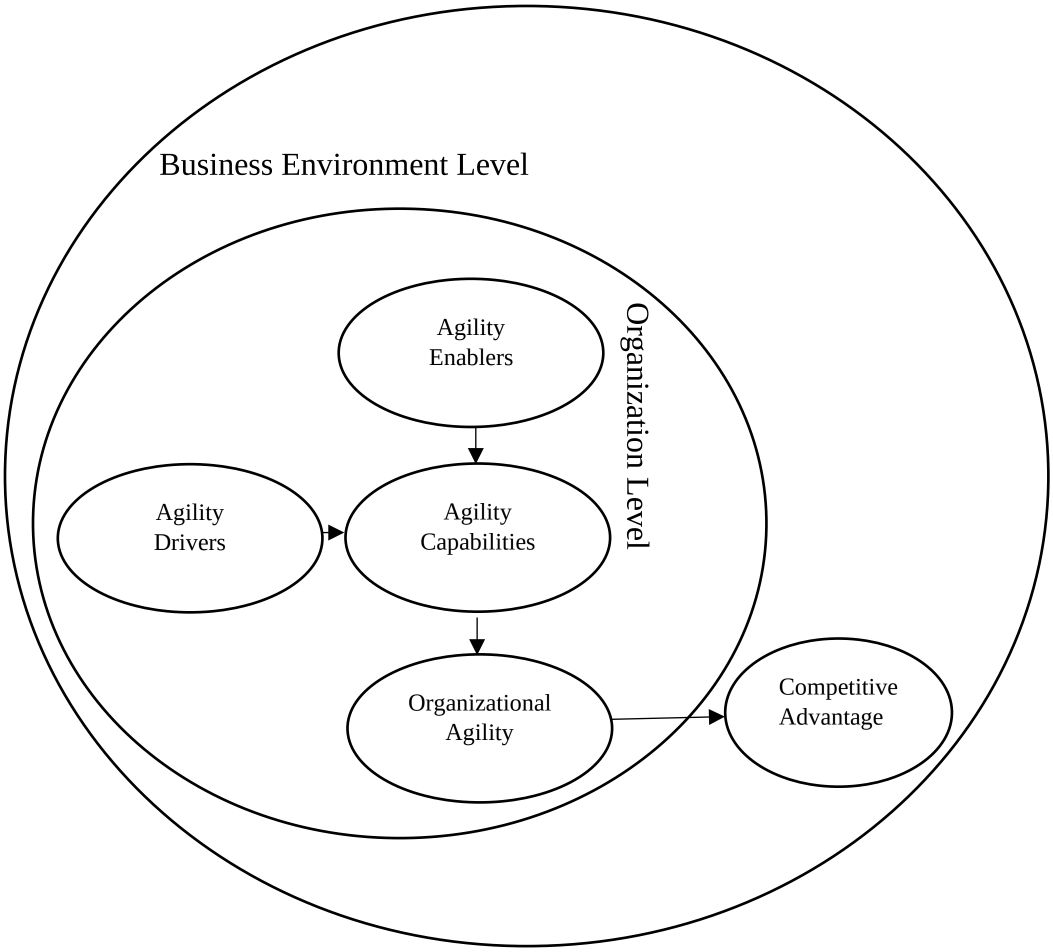

Figure 2.4: Organizational Agility Conceptual Map
Source: designed by the researcher

- *Agility Drivers* discuss the environmental forces that push a firm searching for competitive advantages. Zhang and Sharifi (2000) catigrorized these forces as technology, marketplace, internal complexity, social factors, customer requirements, suppliers, and comptition.
- *Agility Enablers* define practices, methods, tools, and technologies that facilitate organizational agility (Bessant et al., 2000; Lin et al., 2006; van Oosterhout et al., 2006). Vinodh and Aravindraj (2012) assingned agility enablers to five culusters: maufacturing management, manufacturing strategy, management responsibility, labour force, and technology.

- *Agility capabilities* are specified abilities provide requisite power to respond to changes. Lee et al. (2015) explained four capabilities that required to exploit market opportunities earlier than competitors, which are responsiveness, proactiveness, adaptiveness, and radicalness. A quick reaction to the market due to changes in demands or environment uncertainties is made possible through responsiveness (Hult et al., 2005). Proactiveness represents forward-thinking and anticipation to seize new marketplace opportunities ahead of market player (Lumpkin & Dess, 1996; Miller & Friesen, 1983). Adaptiveness, is identifying best practices on the market synchronizing with these practices (Rindova & Kotha, 2001). The firm's ability to formulate and implement radical business models to pentrate rival's markets is called radicalness (Zahra & Covin, 1995).

2.5.2 The 4S Organizational Agility Framework

As argued by the resource-based view (RBV), dynamic capabilities enable organizations to adjust to their environment. Taking the discussion of the RBV further, the Dynamic Capabilities, consider the routines that allow firms to handle dynamic environment (Eisenhardt & Martin, 2000; Teece et al., 1997). Teece (2007) discusses those routines in terms of sensing, seizing, shifting, and shaping capabilities as shown in Figure 2.3.

1. *Sensing* is the ability to acquire opportunity and detect threats, from the internal and external environment.
2. *Seizing* is proper decision-making ability on strategy transformation, business model, and organizational boundaries.
3. *Shifting* is successfully applying new capabilities, business model or strategy.

4. *Shaping* is developing the desired capabilities that have measurable impact on the external environment.

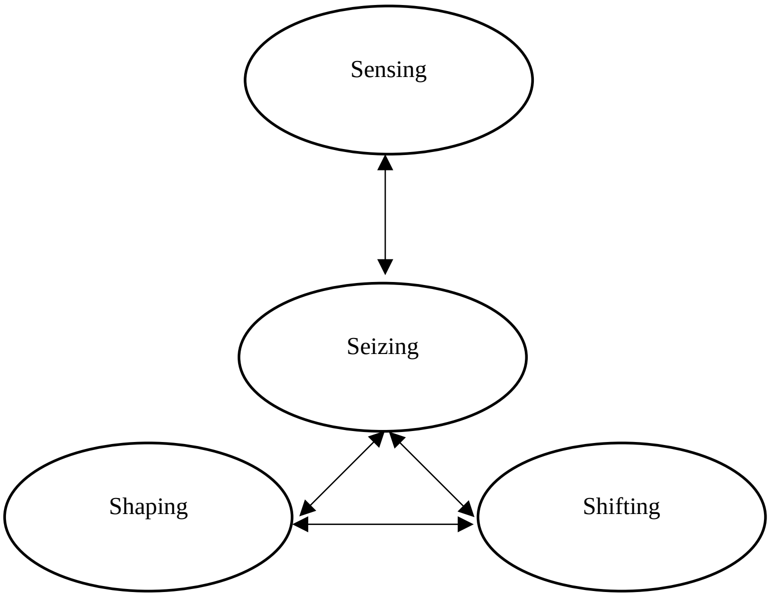

Figure 2.5: The 4S Organizational Agility Framework
Source: designed by researcher

Sensing is essential for environmental scanning process. Explicitly, focuses on the sudden shift in market stakeholders' behaviour (Yang & Liu, 2012). A more proactive sensing approach may lead to scientific and technological outcomes that might shape a new business model and/or update existing one (Appelbaum et al., 2017; Meredith & Francis, 2000). Also, sensing capability has a close connection to searching, where searching is defined as the ability to generate functional knowledge within an organization (internally) to enable entrepreneurial innovation by exploring, exploiting as well as forecasting activities (Baškarada & Koronios, 2017).

Seizing capability forms the cornerstone of the agility framework by connecting and running the other three capabilities. This capability rests on the insights gained through sensing activities. Seizing is responsible for decision making relying on value chain analysis (Porter, 1996), balanced scorecards (Kaplan & Norton, 2008), and, portfolio management (Hedley, 1977). Decision-making can simplify organizational transformation under uncertainty (Baškarada & Koronios, 2017). Seizing is also considered as input for shifting and shaping capabilities through ongoing governing of related transformational activities, while providing continuous measuring and assessing.

Shifting is about moving from a status-quo to a new planned state. This may have commonalities with offering of new products and services (Leonard-Barton, 1992), horizontal and vertical integration strategies (Soosay et al., 2008), adjustments to the business model (McIvor, 2000), and productivity enhancements through innovation adoption (Brynjolfsson & Hitt, 2000). In this respect, shifting capability drives to gradual changes, which are assessed via shaping and revising through seizing. This means that harmonization between capabilities is indispensable to a greater magnitude shift.

Shaping is substantially related to operational effectiveness, efficiency and scalability, which include resource acquisition, production planning, demand management, and quality control (S. Gupta & Starr, 2017). In other words, this dynamic capability is responsible for creating innovative internal opportunities that have tangible effects on the external environment.

2.5.3 Agility in Manufacturing Context

The manufacturing sector is in front of a severe competition due to globalization that fueled the customers’ appetite for innovative products with high quality and reasonable price (Dubey & Gunasekaran, 2015; Goswami & Kumar, 2018). In a volatile business environment, manufacturing firms need to adopt revolutionary tactics relating to production cycle (Cheng et al., 1998), in order to achieve and sustain their organizational objectives (Iqbal et al., 2018). These tactics entail re-engineering a firm’s strategy, structure and culture (Vázquez-Bustelo et al., 2007). The paradigm of “Agile manufacturing” has engaged the attention of specialists due to its role in performance enhancement and sustainable competitive advantage (Bottani, 2010). With the advent of agile manufacturing (AM), companies come into the ability to react dynamically to unforeseen demands of the customer (Ajay Guru Dev & Senthil Kumar, 2016). Agile manufacturing as a concept was coined for the first time in 1991 in the research titled ‘‘21st Century Manufacturing Enterprise Strategy” (Khoo & Loi, 2002; Sharma et al., 2022).

Gunasekaran (1998, p. 1223), defined agility manufacturing as: “*the capability to survive and prosper in a competitive environment of continuous and unpredictable change by reacting quickly and effectively to changing markets, driven by customer-designed products and services*”. The core of "Agility Manufacturing" term includes change in organizational culture to master uncertainty and change (Aravind Raj et al., 2014; Ren et al., 2003), empowerment of organization members (Gore et al., 2009; Meade & Sarkis, 1999), customer enrichment (Dubey & Gunasekaran, 2015; Meade & Sarkis, 1999), and cooperation to enhance attractiveness (Sharifi & Zhang, 1999). In the age of industry 4.0, the agile manufacturing practices are considered as integral part of day-to-day activities (Kumar et al., 2020). It emphasises on flexibility, cost, product customisation, technology usage, market share, customer loyalty and profitability (Gunasekaran et al., 2019). AM is best methodology for the market conditions with product characteristics like high variety, small volume, short life cycle (Rehman et al., 2019). Vazquez-Bustelo et al. (2007) revealed that AM has improved the operational, financial, and market performance of the firm, consecutively promoting competitive strength. Alike, Kumar et al. (2020)and Gunasekaran et al. (2018) find out that successfully implementing of “Agility Manufacturing” responsible for competitiveness returns.

2.6 Theoretical Framework

The proposed research model of the current study demonstrates the relationship between big data analytics capability (BDAC) and organizational agility (OA) through entrepreneurial orientation (EO). We grounded on the resource-based view framework (RBV) and its extension, dynamic capability theory (DCT) to study the relationship. The following sections present our proposed theoretical model:

2.6.1 Hypothesis Development

2.6.1.1 Big Data Analytics Capabilities and Organizational Agility

BDA has recently received substantial attention from firms as a tool to manage the proliferation in digital transformation and unprecedented availability of data. As the use of the internet and social media surge, there is unprecedented amount of data that are accumulated (Jianzheng Liu et al., 2016). Many firms try to establish a stronger relationship with their customers beyond simple transactions. Through customer relationship management systems, they can gauge customer interactions and accumulate longitudinal data.

The firms that can build the big data analytics capabilities can quickly sense their market changes, leverage threats and opportunities, and make decisions quickly and accurately (Hyun et al., 2020; Mandal, 2018; Zhou et al., 2018). For instance, prompt access to information enables firms to recognize changes in behaviours of their competitors, reception of technological advancements, and customer preferences. Subsequently, those that have this access to the information can gain actionable insights within their managerial teams (Lu & Ramamurthy, 2011). In particular, data analytics enables quick responses and better quality and timely decisions thus increased the agility leading to developing and producing products and/or services that address customer expectations without delay (C. Cheng et al., 2020; L. Li et al., 2020). Furthermore, the adoption of the data analytics results can increase operational adjustment agility. This kind of agility occurs as a result of business process optimization within a firm allowing to enhance its ability to rapidly respond to the changing environment in a competitive manner (Ghasemaghaei et al., 2017). With reference to dynamic capabilities theory, big data analytics can be considered as the analytical skill that enhances firm’s decision-making process under uncertain circumstances (Y. Chen et al., 2015). This finding is in line with the essence of dynamic capability literature asserted that higher-order capability (e.g. organizational agility) derives from a bundle of lower-order capabilities such as big data analytics (Ashrafi et al., 2019; Ayabakan et al., 2017; Ghasemaghaei et al., 2017; Sambamurthy et al., 2003). Thus, we put forward:

H1: Big data analytics capabilities have a positive relationship with organizational agility.

2.6.1.2 Big Data Analytics Capabilities and Entrepreneurial Orientation

In dynamic market conditions, competitive advantage depends on big data analytics capabilities to better realize customer desires (Duan et al., 2020). Entrepreneurial orientation refers to a firm's proclivity to explore new business opportunities in the current and/or new markets that may offer advantages to the firm (Boso et al., 2013). The entrepreneurial conduct exhibited by the firm is commonly focused on how firms run their business activities and reflects their core thinking (B. A. George & Marino, 2011; Miller, 1983). Wu (2008) argues that entrepreneurial capabilities are one of the key elements that aid firms in the dynamic environment. Three main characteristics of innovativeness, risk-taking, and pro-activeness enable entrepreneurially oriented firms to access new customers through innovative products and technology (Miller, 1983). Since the innovation is generally a costly and risky investment, firms need to leverage big data analytics capabilities to reduce cost of the innovation process and generate superior returns (Arunachalam et al., 2018; Johan Wiklund & Shepherd, 2005). Consequently, both big data analytics and entrepreneurial orientation empower organizations to enhance the value they provide to their customers and thus gain competitive advantage by offering differentiated products and services or offering lower prices than the competition for their customers. Therefore, we posit:

H2: Big data analytics capabilities have a positive relationship with entrepreneurial orientation.

2.6.1.3 Entrepreneurial Orientation and Organizational Agility

The core of entrepreneurial orientation (EO) is the strategic actions for creating business value in response to challenges and opportunities in the environment (Lumpkin and Dess, 1996; Rauch et al., 2009).

EO establishes the road-map for higher organizational agility despite hostile economic conditions (Christopher, 2000). Firms with high levels of entrepreneurial activities are likely to organize their resources in an agile way in volatile markets (Zahra et al., 2009). Agile firms quickly and effectively sense potential market demands, adjust the needed resources to innovate new solutions and change competitive directions in a short while and leaving themselves space to manoeuvre in other paths (S. H. Kim et al., 2015; Sambamurthy et al., 2003). The debate of entrepreneurship in relation to organizational agility leads to an inference that EO and agility are theoretically and practically considered as related concepts in the organization development field. In this sense, we hypothesize:

H3: Entrepreneurial orientation is positively associated with organizational agility.

2.6.1.4 The Mediating Role of Entrepreneurial Orientation

Information technology (IT) literature indicates that dynamic capabilities (i.e. entrepreneurial orientation) can establish a connection between knowledge management and agility in organizations (Ashrafi et al., 2019; Ghasemaghaei et al., 2017; Hyun et al., 2020). As stated in Watson et al. (2018), a culture driven by big data fosters knowledge access and the sharing of information that support organizations' analytical capabilities. Subsequently the access and sharing of information and the removal of "silos" helps to develop an entrepreneurial climate. Furthermore, successfully acquiring real-time data on market players can help firms to predict current and potential future behavior of their competitors and customers in the market where they compete, thus augmenting their ability to seize the calculated risks for promising development opportunities (Côrte-Real et al., 2017). Several studies in the field of information technology address the positive effects of big data analytics on entrepreneurial orientations (OE) and, in turn, on agile, competitive advantage, and overall performance. According to Qosasi et al. (2019) information systems capabilities encourage entrepreneurial orientation by empowering innovative, risky, and proactive decisions in a volatile market, which increase their competitive advantage. Similarly, Sahi et al. (2019) stated that technological development levels govern the effects of entrepreneurial efforts on operational responsiveness. That is, entrepreneurial efforts can foster manufacturing ability to observe favorable market needs, which directly influence business overall performance (Chavez et al., 2017). Innovation dimension of EO leads to increase in flexibility of production volume, product assortment, and offering new products (S. Chang et al., 2007). Whereas proactive dimension facilitates scanning firm's business environment to develop and offer novel products and change currently used tactics and strategies (G.T. Lumpkin & Dess, 1996). Accordingly, we expect:

H4: Entrepreneurial orientation mediates the relationship between big data analytics capabilities and organizational agility.

Chapter 3

RESEARCH METHODOLOGY

3.1 Introduction

In scientific research, methodology focuses on the research tool and procedure to attain the required data for the study (Opoku et al., 2016). Further, it helps readers to judge the overall quality of the research study. This chapter explains research methodology which will be used in this study. More specifically, in this chapter researcher highlights the research questions, population and sample, data collection process, research instrument and measurements, and ethical assurances.

3.2 Research Questions

This study aims to reveal the mechanism of the relationship between big data analytics capability and organizational agility in the manufacturing industry through attempting to answer the following:

Q1: How do big data analytics capabilities (BDAC) impact organizational agility (OA)?

Q2: What role does entrepreneurial orientation play in the big data analytics capabilities - organizational agility relationship?

The sample population of this study will be companies within the manufacturing industry in Jordan.

3.3 Population and Sample

3.3.1 Population

The research population is defined as the whole set of entities that the researcher wishes to be able to generalize to in their study with a goal to understand it and draw an inference (Salkind, 2010). The target population of this study will be companies within the manufacturing industry in Jordan. According to the database of Jordan chamber of industry there are total of 2645 manufacturing companies.

3.3.2 Sample

Sampling is a scientific instrument for locating a representative sample from a target determinate population (J. K. Kim & Wang, 2019). Choosing proper sampling technique is very important because data help in understanding theoretical framework of the research which is the pillar of any investigation (Etikan et al., 2016). This dissertation used random sampling technique. Random sampling delivers the better estimate of research parameters in comparison to purposive sample (Singh et al., 2014). The sample size has been determined using the inverse square root formula (Joseph F. Hair et al., 2021):

$$\textit{Significance level 5\%: } n_{min} > (2.486 / |p_{min}|)^2$$

n_{min} = minimum sample size.

p_{min} = the value of the minimum significant path coefficient, that is (0.2).

$n_{min} > (2.486 / |0.2|)^2 = 154.505 \approx 155$ firms.

3.4 Data Collection Process

Questionnaires were circulated to 335 top-level managers in relevant firms between December 2020 and February 2021. The decision to targeting the top-level managers was made since top-level managers are more informed of the issues relating to the firm’s strategy and decision–making process. We received 104 complete and usable questionnaires, resulting in an effective response rate of 31 percent. Baruch and Holtom (2008) pointed out the average response rate for studies that targeted top management or organizational representatives was 35.7 percent with a standard deviation of 18.8, which means 68 percent of the response rate fall within 16.9 percent and 54.5 percent. Furthermore, a medium effect size requires a sample size of at least 38 cases calculated using inverse square root method with a significance level of 5 percent and at a power level of 95 percent (Kock & Hadaya, 2018). Hence, our sample size is sufficient for model assessment. Non-response bias was tested comparing early response (first three weeks) and late responses (last three weeks) using paired t-test (Armstrong & Overton, 1977). The results articulate that there is no statistically significant difference among the groups of response ($p > 0.05$).

3.5 Research Instrument and Measurements

3.5.1 Instrument Development

To test our hypothesized model, we developed a questionnaire, operationalized our constructs using measures that had been developed and tested for their validity and reliability in the relevant literature (Flynn et al., 1990). The Arabic translation of the measures were also translated back to English language to check for equivalence of meaning with the original measures and items.

The face-validity of the measurement was assessed by two professors and four general managers who were asked to review the questionnaire clarity and structure. Based on the feedback, necessary adjustments to the items were made to ensure that the measures would maintain the same meaning and be understood by the sampled respondents. The respondents rated all items on a Likert scale where the response options ranged from Strongly Disagree (1) to Strongly Agree (5).

3.5.2 Measures

Overall, 40 items were selected from formerly validated items to measure the constructs of our hypothesized model. The measures used were:

3.5.2.1 Big Data Analytics Capability Items

BDA capabilities was measured as a higher order reflective construct consisting of five reflective subscales namely, Data-driven Culture, Organizational Learning, Management Skills, BDA Infrastructure, Technical Skills. Each subscale was made up of four items and adopted from Belhadi et al. (2020) and Gupta and George (2016).

The items used to measure BDA Capabilities higher order variable included phrases such as ‘decision making process based on big data analytics is part of firm culture’ for the Data-driven Culture subscale; ‘employees eager to transfer their knowledge about big data analytics’ for Organizational Learning subscale; ‘managers can evaluate the outcomes of big data analytics to accelerate decision-making’ for Management skills subscale; while ‘firm has flexible data management infrastructure (e.g. software, hardware, data, and networks)’ for BDA Infrastructure subscale; ‘firm hires skilled people on big data analytics’ for Technical Skills subscale.

Belhadi et al. (2020) reported statistically adequate construct reliability coefficient CR (composite reliability), that is, .82 for Data-driven Culture, .75 for Organizational Learning, .77 for Management Skills, .78 for BDA Infrastructure, .75 for Technical Skills. Similarly, our construct reliability results are α = (.74, .83, .90, .85, .85) respectively. The alpha value for the whole (higher order construct) is .86.

3.5.2.2 Entrepreneurial Orientation Items

We measured Entrepreneurial Orientation using fourteen items adopted from Niemand et al. (2020), Acosta et al. (2018), and Al Mamun and Fazal (2018). The Entrepreneurial Orientation was a higher order construct that was made up of three reflective latent subscales: Innovativeness measured with five items such as ‘firm prioritizes to invest on new projects rather than sitting and waiting for someone else to do’, Pro-activeness measured with five items such as ‘top management always promotes ideas of novel products for markets’, and Risk Taking measured with four items such as ‘firm tends to act boldly in situation where risk is involved’. In Niemand et al. (2020) study the subscales of Entrepreneurial Orientation had Cronbach’s Alpha values of .87 for Innovativeness, .84 for Proactiveness, and .69 for Risk-taking. The reliability construct coefficient (α) of this study is .88, .82 and .80 respectively for the subscales, while the whole reliability for higher construct is α = .70.

3.5.2.3 Agility Items

Since we made use of agility as a second order reflective construct to assess firm agility, we adopted six-item scales from Li et al. (2020); Mao et al. (2020) that formed two latent constructs Market Capitalizing Agility (three items such as ‘firm deals with market-related chaos as an opportunity to capitalize on them rapidly’) and Operational Adjustment Agility (three items such as ‘whenever there is a disruption in supply chain from suppliers, firm can quickly adopt the alternative internal adjustment’).

Mao et al. (2020) indicated strong construct reliability values with an alpha of .87 for Market Capitalizing Agility and .89 for Operational Adjustment Agility. The reliability values in our study are α= .71 for Market Capitalizing Agility and 0.72 for Operational Adjustment agility. Also, the whole reliability coefficient is α = .80.

3.6 Ethical Considerations

Whenever we interact with other individuals, we must give their emotional needs and rational concerns foremost importance, since it will shape their responses to our acts. This study was guided by the ethical principles of research set out by Eastern Mediterranean University. Appendix (A) provides the ethical approval, which is necessary to start the data collection process. The covering letter (Appendix B) was attached with survey questionnaire to provide information on the research to make sure the participants aware of the whole project before agree or decline to join. The data have been confidentiality treated; no data were issued or used for the purposes outside the scope of the study. Also, avoid plagiarism wherever possible and research misconduct (falsifying data, manipulating data analysis, corrupting results), received plentiful attention from the researcher.

Chapter 4

RESEARCH FINDINGS AND ANALYSIS

4.1 Introduction to Finding and Analysis

This study uses PLS-SEM using confirmatory composite analysis approach and SmartPLS (v.3.3.3) software package to assess the research model's validity, reliability, and research hypotheses (Joe F. Hair et al., 2020; C M Ringle et al., 2015). PLS-SEM was considered suitable for this study for several reasons. The PLS-SEM is now widely used and provides flexibility with respect to theory-building and practice (Richter et al., 2016). PLS-SEM has an ability to address small sample sizes (Hair Jr et al., 2016), which this study has. The PLS-SEM enables the analysis of categorical and numerical dataset with non-normal frequency distribution (Nair et al., 2018). Furthermore, PLS-SEM is useful to predict models with higher-order constructs (Lohmöller, 1989; Christian M Ringle et al., 2020).

The arrangement of the findings is as follows, first we present the demographic information of the respondents, second is the assessment of the measurement model to see the reliability and internal consistency, convergent and discriminant validity of the constructs/scales and the items that form them, the third is the descriptive analysis of the constructs used, then, the assessment of the structural model to examine the path coefficients linking our study variables, the R2 explaining the amount of variance explained in our endogenous variables, the effect size f2 and predictive relevance Q2 (Joseph F. Hair et al., 2019) of the research, and finally, is the post hoc analysis.

4.2 Demographical Analysis of the Respondents

Table 4.1 and its visualization Figure 4.1 present the profile of participating firms. The majority of the respondents are firms with capital less than 500.000 Jordanian Dinar (49%). In terms of full-time employees, 67.8% of firms had 50 hands and more, whereas 53.8% of them have been experiencing over 15 years. Furthermore, our study sample represents all manufacturing sub-sector.

Table 4.1: Characteristics of responding firms (N = 104)

Category	Frequency	Percentage
Firm's capital (JD)		
Less than 500,000	51	49
500,000 -1,000,000	14	13.5
Over 1,000,000	39	37.5
Full time employees		
Fewer than 10	6	5.8
10 – 49	28	26.9
50 – 249	38	36.5
Over 249	32	30.8
Firm’s years of experience		
Fewer than 5	9	8.7
5 – 10	21	20.2
11– 15	18	17.3
Over 15	56	53.8
Industry sector		
Garments & Leather	15	14.4
Pharmaceuticals & Medical Supplies	5	4.8
Chemicals & Cosmetics	8	7.7
Plastics & Rubber	13	12.5
Engineering & Electronics	11	10.6
Wood & Furniture	3	2.9
Construction	8	7.7
Agri-Business & Agro-Processing	17	16.3
Packaging & Paper	15	14.4
Extraction	9	8.7

Notes: The industry sectors are presented according to Jordan chamber of industry.

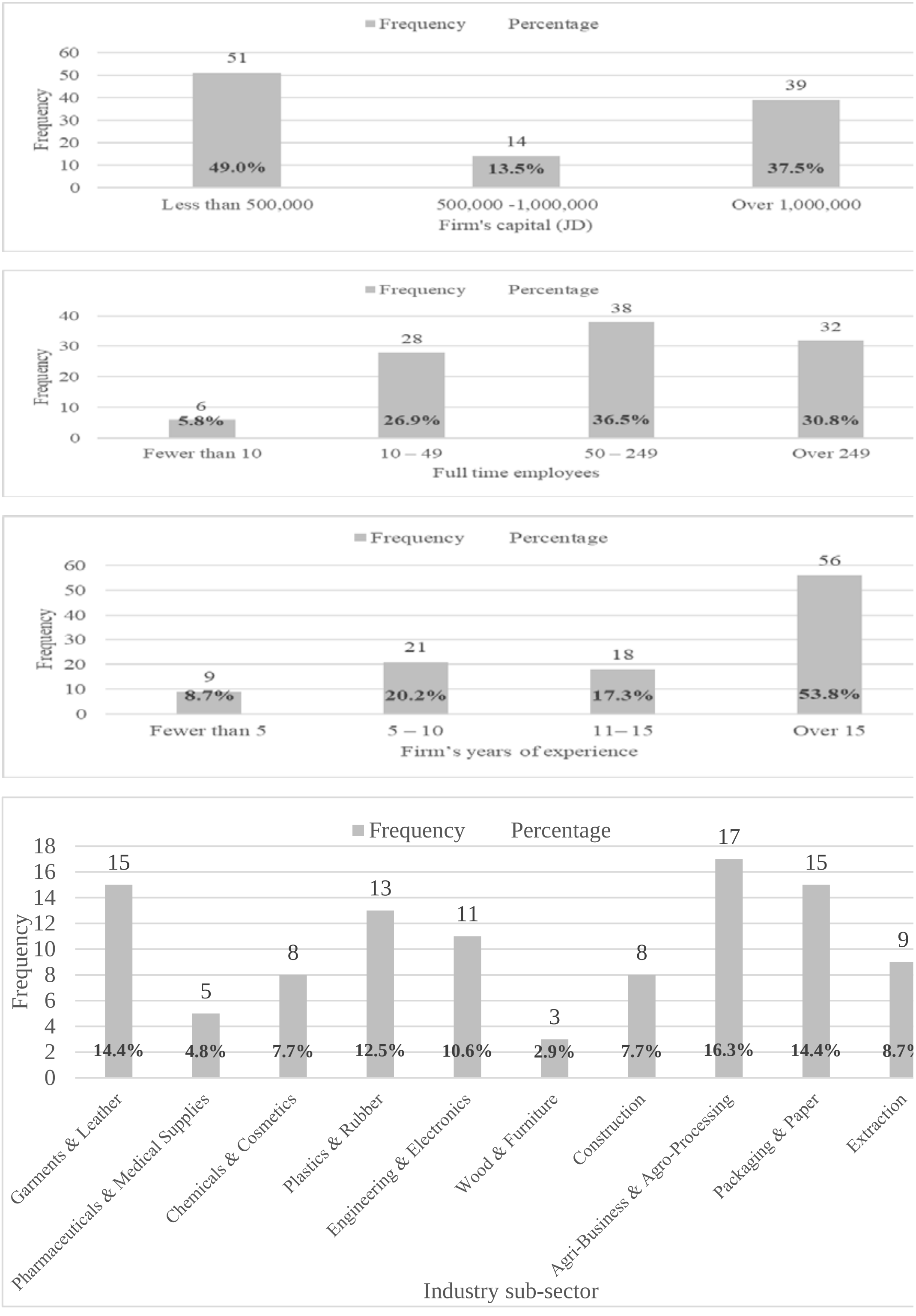

Figure 4.1: Summary for Demographical Analysis

4.3 Descriptive Analysis

In this part we present frequency distribution information of the participants responses such as mean, standard deviation, ranking and convenience level for each measurement item constructs the study variables. This study adopted three convenience levels (high, moderate, weak) to interpret the arithmetic mean, based on the following formula guided by a Likert scale (strongly disagree (1); disagree (2); neutral (3); agree (4); strongly agree (5)):

Interval length = (maximum - min) / number of levels = (5– 1) / 3 = 1.33. Thus, the three convenience levels are as follows: (1) weak: 1–2.33; (2) moderate: 2.34–3.66; (3) high: 3.67–5.

4.3.1 Data Driven Culture (DDC)

Table 4.2: Descriptive analysis for DDC

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
DDC1	Our firm considers data as an asset.	4.279	0.794	1	High
DDC2	Our employees base most decisions on data rather than instinct.	4.067	0.855	3	High
DDC3	We regularly improve the business decision making processes in response to the insights obtained from data.	4.240	0.717	2	High
DDC4	Decision-making process based on big data analytics is part of our organizational culture.	4.019	0.744	4	High
	Overall average	**4.151**			**High**

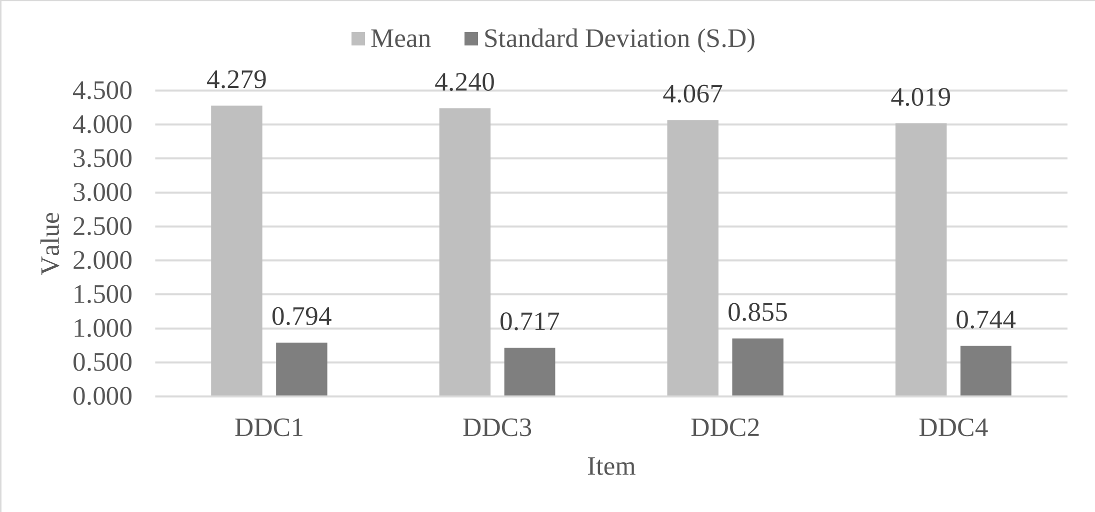

Figure 4.2: Mean Values for Data Driven Culture

The above table and figure show descriptive data for the data driven culture items. The overall average of the construct was (4.151), and this reflects a high level of convenience, and the standard deviation ranged between (0.717–0.855). Also, DCC1 was the most assenting item, with an arithmetic average of (4.279), this could be attributed to firms perceive the importance of the data in their operations.

4.3.2 Organizational Learning (OL)

Table 4.3 and pertaining Figure 4.3 present the descriptive analysis results of the organizational learning items. The overall average of the construct was (3.873), and this indicates a high level of convenience, and the standard deviation ranged between (0.782–0.989). The results reveal convergence of the mean values of responses, which may return to the fact that “knowledge is power”.

Table 4.3: Descriptive analysis for OL

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
OL1	Big data analytics knowledge is shared within the firm.	3.990	0.782	1	High
OL2	Our employees are eager to transfer their knowledge about big data analytics.	3.827	0.853	3	High
OL3	Our employees' feedback about big data analytics are systematically reviewed.	3.798	0.989	4	High
OL4	Our staff is able to acquire new big data analytics knowledge.	3.875	0.855	2	High
	Overall average	**3.873**			**High**

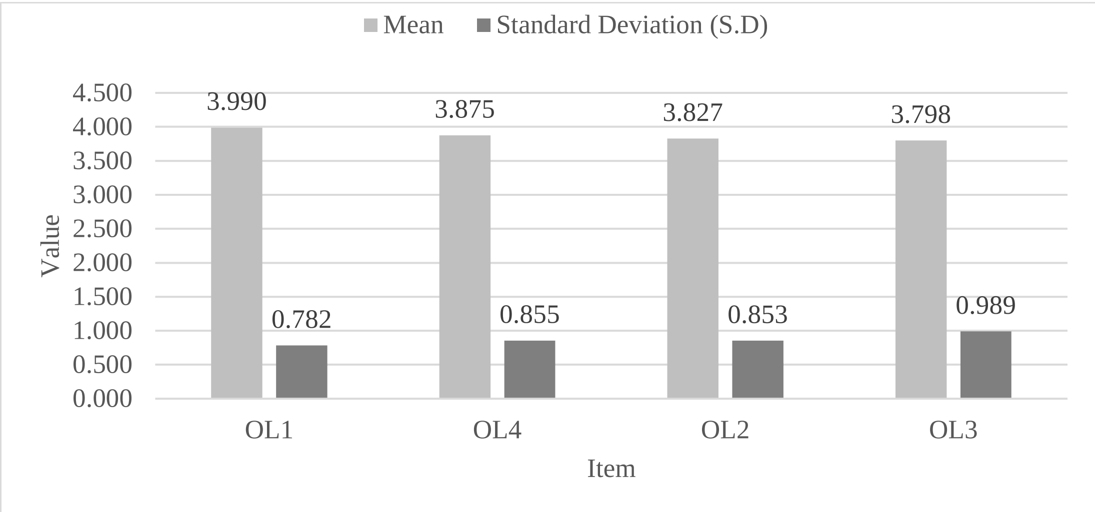

Figure 4.3: Mean Values for Organizational Learning

4.3.3 Technical Skills (TS)

Table 4.4 and its related Figure 4.4 show the descriptive analysis for technical skills. The overall average of the construct was (3.697), and this indicates a high level of convenience, and the standard deviation ranged between (0.910–1.140). Additionally, TS4 was the most acquiescent item, with an arithmetic average of (4.077), the reason could refer to that investigated firms have skilled workers.

Table 4.4: Descriptive analysis for TS

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
TS1	We invest in the latest technologies of big data analytics.	3.480	1.149	4	Moderate
TS2	Our firm hires high-skilled people on big data analytics.	3.490	1.140	3	Moderate
TS3	Our firm provides training to improve the technical skills of employees.	3.740	1.166	2	High
TS4	The technical skills owned by our own employees assist to accomplish their jobs effectively.	4.077	0.910	1	High
	Overall average	**3.697**			**High**

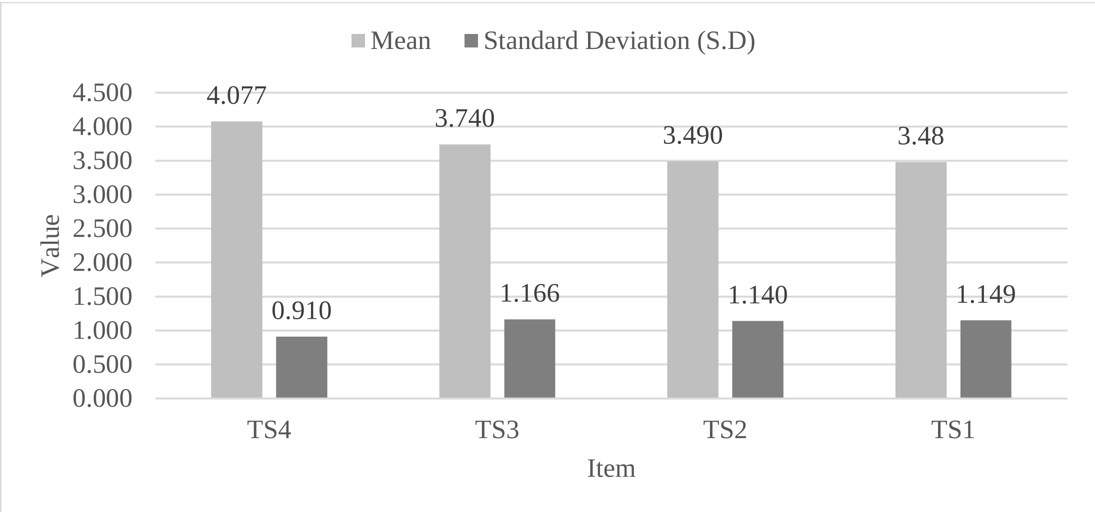

Figure 4.4: Mean Values for Technical skills

4.3.4 Management Skills (MGS)

The results of management skills items (Table 4.5; Figure 4.5) indicate that the overall average of the construct was (3.959), and this indicates a high level of convenience, and the standard deviation ranged between (0.842–0.293).

MGS1 was the most assenting item, with an arithmetic average of (4.096), while MGS2 was the least assenting item, with an average mean of (3.894).

Table 4.5: Descriptive analysis for MGS

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
MGS1	Our managers can evaluate the outcomes of big data analytics to accelerate decision-making.	4.096	0.875	1	High
MGS2	Our managers have a good sense of where to implement big data analytics.	3.894	0.923	4	High
MGS3	Managers in our firm have an ability to evaluate the returns extracted from BDA.	3.904	0.842	3	High
MGS4	Our managers are able to anticipate the future business needs through big data analytics output.	3.942	0.890	2	High
	Overall average	**3.959**			**High**

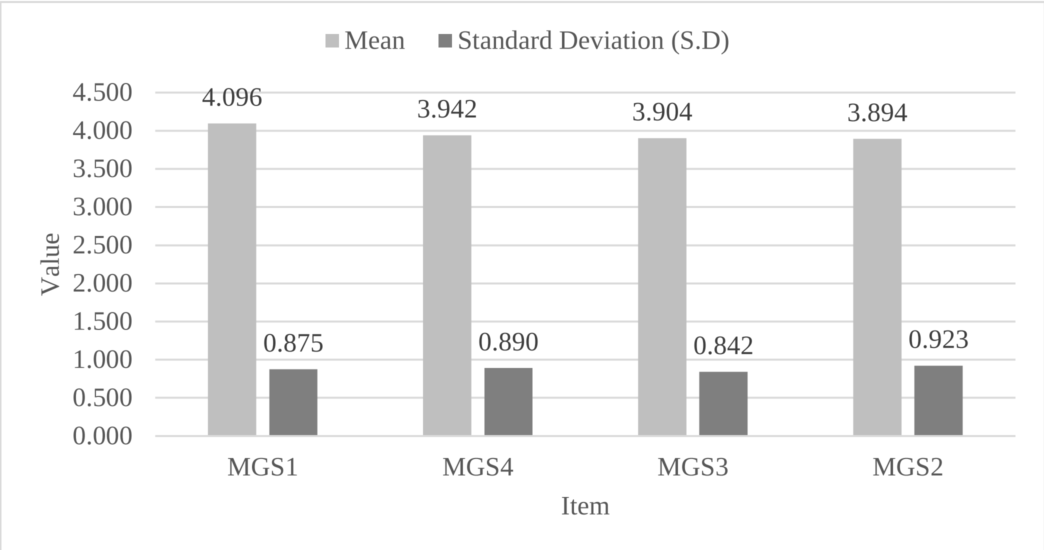

Figure 4.5: Mean Values for Management Skills

4.3.5 Big Data Analytics Infrastructure (BDAI)

Table 4.6: Descriptive analysis for BDAI

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
BDAI1	"Our firm is in the process of implementing or implemented different data visualization tools."	3.682	0.927	2	High
BDAI2	"We are in the process of implementing or implemented data driven sensors."	3.337	1.067	4	Moderate
BDAI3	"We have flexible data management infrastructure (e.g. software, hardware, data, and networks)."	3.962	1.070	1	High
BDAI4	"Our firm has explored or adopted cloud-based services for performing analytics."	3.587	1.267	3	Moderate
	Overall average	**3.642**			**Moderate**

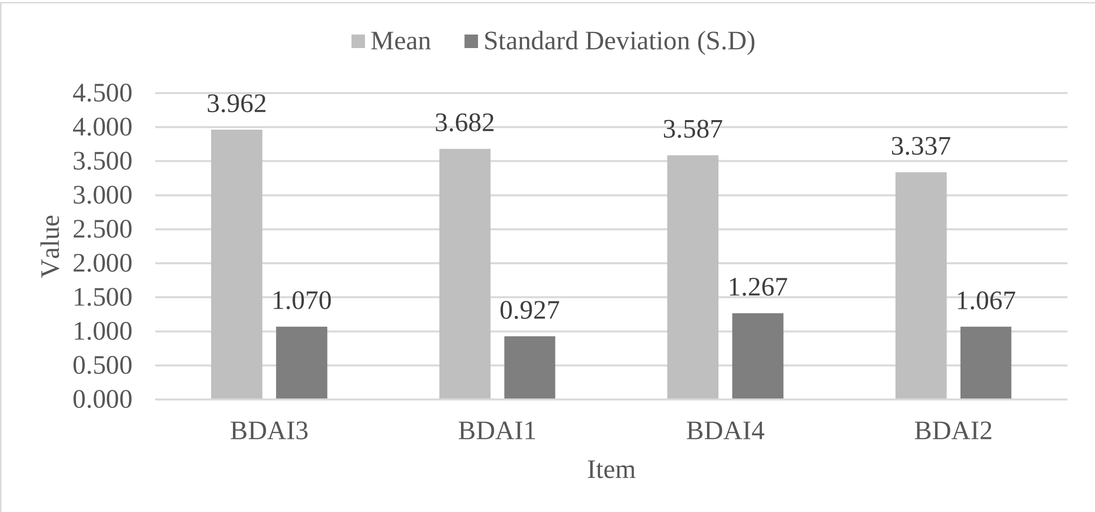

Figure 4.6: Mean Values for Data Analytics Infrastructure

The table and figure above demonstrate the descriptive statistics for big data analytics infrastructure. The overall mean was (3.642), this reflects a moderate level of convenience, and the standard deviation ranged between (0.927–1.267).

The reason behind this level of convenience could be attributed to rapid technological changes, which may reduce the firms’ chance to get the most recent technology in their business's field.

4.3.6 Innovativeness (INO)

Table 4.7: Descriptive analysis for INO

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
INO1	“Our top management always promotes ideas of novel products for markets.”	4.183	0.923	1	High
INO2	“Our top management are very open to innovative initiatives in order to exploit opportunities in market.”	4.106	0.934	2	High
INO3	“We are willing to try unusual solutions in our functional activities.”	3.933	0.948	3	High
INO4	“Our top management continually seeks to raise R&D budget. “	3.673	1.119	5	Moderate
INO5	“When it comes to problem-solving, we support creative solutions more than conventional solutions.”	3.885	0.978	4	High
	Overall average	**3.956**			**High**

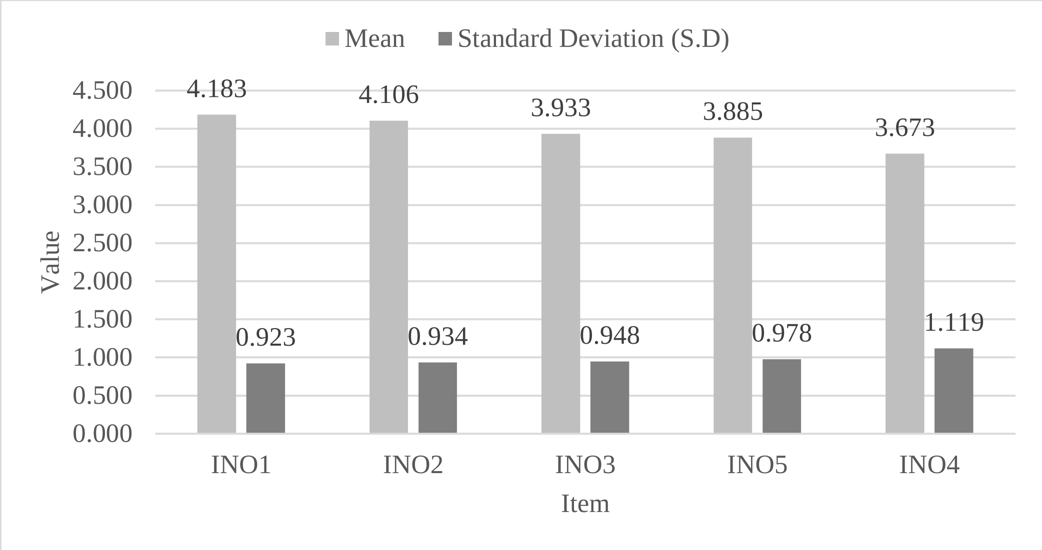

Figure 4.7: Mean Values for Innovativeness

Table 4.7 and Figure 4.7 show the descriptive results for the innovativeness construct. The overall average was (3.956), and this reflects a high level of convenience, and the standard deviation ranged between (0.923–1.119). The INO4 item was the least assenting item, with an average of (4.279), this could refer to the measures taken by firms during covid-19 pandemic where this study performed.

4.3.7 Pro-activeness (PROA)

Table 4.8: Descriptive analysis for PROA

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
PROA1	"In dealing with our competitors, we typically initiate actions competitors respond to"	3.865	0.801	3	High
PROA2	"We have a passion to introduce novel ideas or products prior to rivals."	4.183	0.868	1	High
PROA3	"We are often the first firm to introduce new operating technologies."	3.567	1.022	5	Moderate
PROA4	"We are usually anticipating the future business environment changes."	3.711	0.943	4	High
PROA5	"Our firm prioritizes to invest on new projects rather than sitting and waiting for someone else to do."	3.981	0.914	2	High
	Overall average	**3.861**			**High**

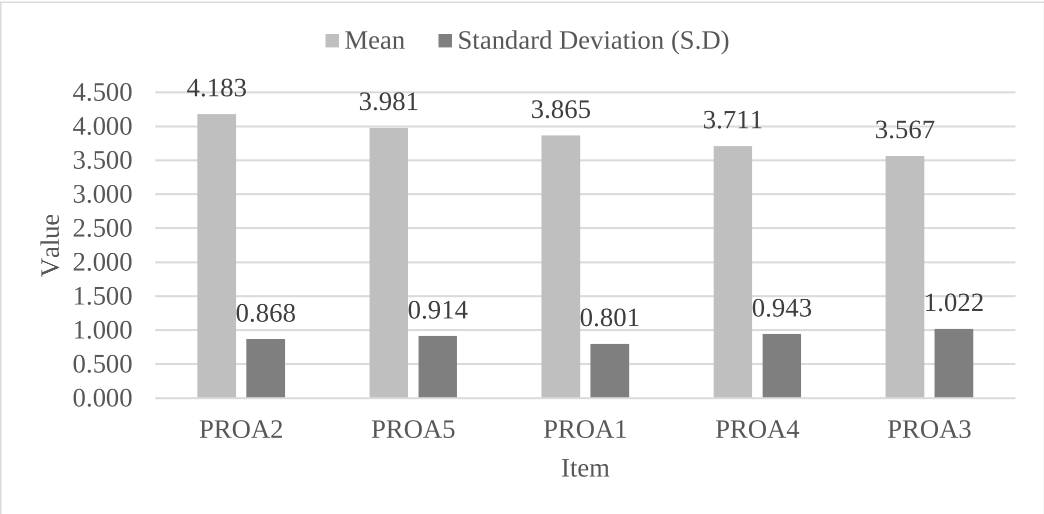

Figure 4.8: Mean Values for Pro-activeness

The results of pro-activeness items (Table 4.8 and Figure 4.8) indicate that the overall average of the construct was (3.861), and this indicates a high level of convenience, and the standard deviation ranged between (0.801–1.022). PROA2 was the most assenting item, with an arithmetic average of (4.183), this may the result of the intense competition into the Jordanian manufacturing industry.

4.3.8 Risk-taking (PROA)

The table and figure below (4.9) display the analysis of risk-taking construct. The overall mean was (3.197), this indicates a moderate level of convenience for the construct items, and the standard deviation ranged between (0.845-1.131). The arithmetic means indicate that the Jordanian firms realize the benefits of risk-taking but don’t adopt it broadly.

Table 4.9: Descriptive analysis for risk-taking

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
RISK1	“Our firm has a strong preference for risky projects.”	3.058	1.131	3	Moderate
RISK2	“we believe that bold actions are necessary to achieve the firm’s objectives.”	3.817	0.845	1	High
RISK3	“We accept taking out bold action by venturing into the unknown.”	2.837	1.080	4	Moderate
RISK4	“Our firm tends to act boldly in situations where risk is involved.”	3.077	1.129	2	Moderate
	Overall average	**3.197**			**Moderate**

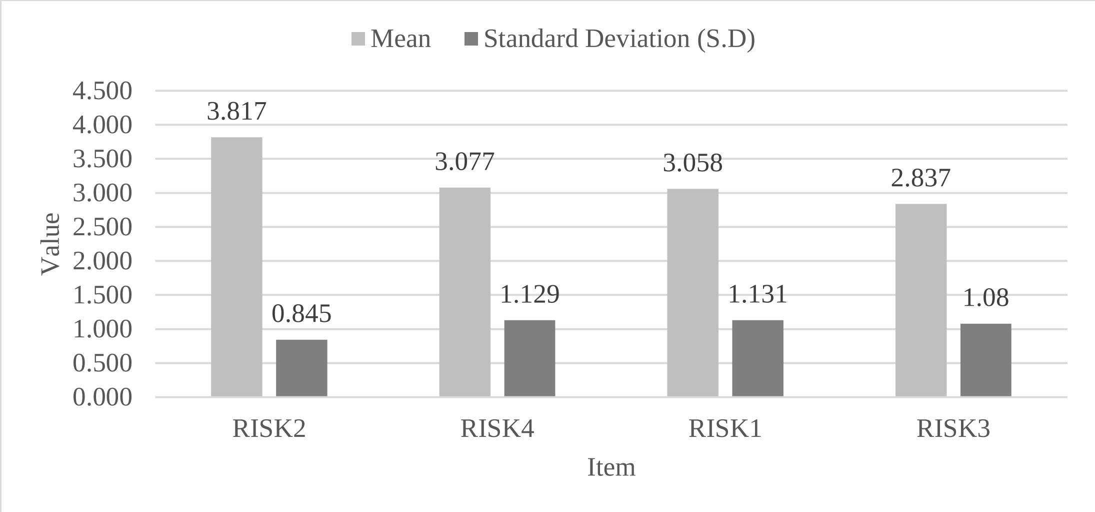

Figure 4.9: Mean Values for Risk-taking

4.3.9 Market Capitalizing Agility (MCA)

Table 4.10: Descriptive analysis for MCA

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
MCA1	"Our firm deals with market-related chaos as opportunities to capitalize on them rapidly."	3.846	0.856	3	High
MCA2	"We are quick to apply appropriate decisions in the face of market/customer changes."	4.009	0.865	2	High
MCA3	"our firm permanently looks for ways to reinvent/re engineer its business to better serve our target market."	4.077	0.844	1	High
	Overall average	**3.977**			**High**

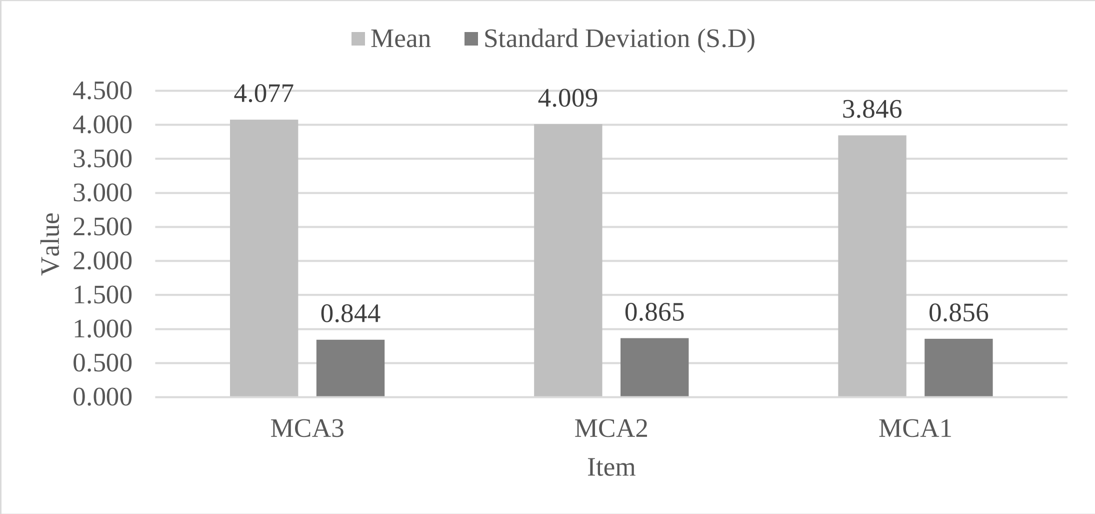

Figure 4.10: Mean Values for Market Capitalizing Agility

Table and figure (4.10) show the descriptive analysis for market capitalizing agility. The overall average of the construct was (3.977), and this indicates a high level of convenience, and the standard deviation ranged between (0.844-0.856). Additionally, MAC3 was the most acquiescent item, with an average of (4.077).

4.3.10 Operational Adjustment Agility (OAA)

Table 4.11: Descriptive analysis for OAA

Item	Description	Mean	Standard Deviation (S.D)	Ranking	Level
OAA1	“Whenever there is a disruption in supply chain from our suppliers, we can quickly adopt alternative internal adjustments.”	3.980	0.935	2	High
OAA2	“Our firm can quickly scale up or down production/ service levels to support fluctuations in the market demand.”	4.183	0.973	1	High
OAA3	“We rapidly fulfill demands of our customers; our customers have confidence in our ability.”	3.519	0.763	3	Moderate
	Overall average	**3.894**			**High**

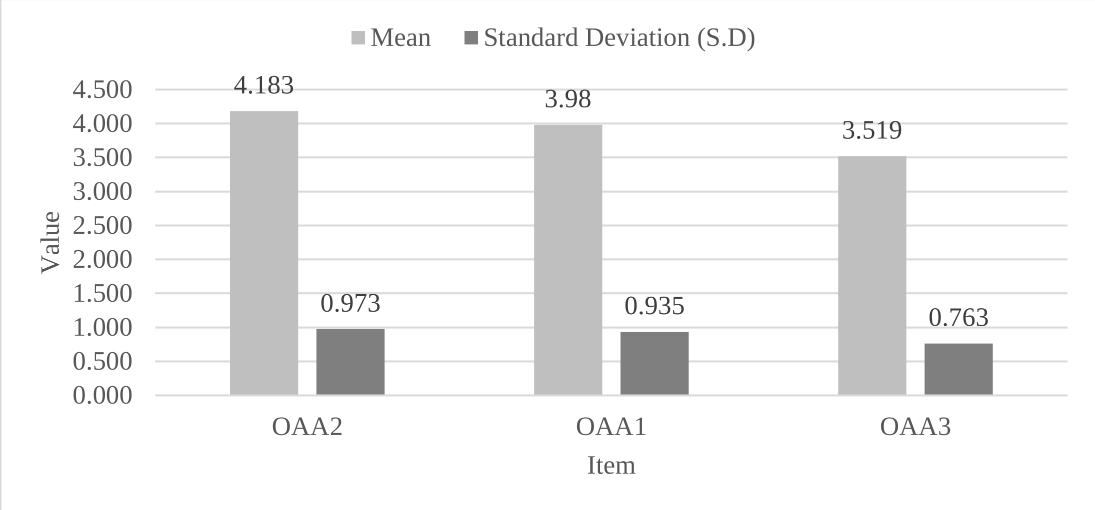

Figure 4.11: Mean Values for Operational Adjustment Agility

The results in table and figure (4.11) reveal that the overall mean was (3.894), and this indicates a high level of convenience and the standard deviation ranged between (0.763-0.973). The least asserting item was OAA3 with a mean of (3.519), this could be attributed to fulfilling market demands rapidly relies on the manufacturing process and technology used by a firm.

4.4 Measurement Model Analysis

To examine indicators internal consistency, we opted to consider the loadings above the acceptable level 0.5 (Joseph F. Hair et al., 2019). All indicators show good internal consistency, as all the loadings explain more the 50 percent of the indicator's variance (see Appendix C and D). Constructs reliability was estimated using composite reliability and ρ_A, the coefficient should be between 0.7 and 0.9 (Dijkstra & Henseler, 2015; J. Hair et al., 2017). We assessed the convergent validity using the average variance extracted (AVE) using a threshold of 0.50, which means that each construct explains at least 50 percent of the variance of its items (Fornell & Larcker, 1981; Hair Jr et al., 2016). The resulting ρ_A, composite reliability, and AVE values (see Table 4-12) are above the threshold. We further established the discriminant validity via two means. First, used Fornell-Larcker approach to verify that the square root of the construct AVEs gives a higher value than the inter-constructs correlation value. Figures 4.12, 4.13, 4.14 illustrate positive relationship between the study constructs (big data analytics capability, entrepreneurial orientation, organizational agility). Second, the Heterotrait-Monotrait ratio (HTMT) test proposed by Henseler et al. (2015). The value less than 0.85 or 0.90 at 95 percent confidence interval indicates sufficient discriminant validity (Franke & Sarstedt, 2019; Joseph F. Hair et al., 2019; Voorhees et al., 2016). Table 4.13 and Table 4.14 report that all constructs are independent of each other. Hence, the criterion for discriminant validity has been met. In sum, based on these results we can assert that our measurement model has sufficient level of indicators reliability, and construct convergent and discriminant validity.

Table 4.12: Reliability and validity statistics.

Construct	ρA	Composite reliability (CR)	Average variance extracted (AVE)
Data-Driven culture	0.74	0.84	0.56
Organizational learning	0.83	0.89	0.66
Technical skills	0.85	0.90	0.69
Management skills	0.90	0.93	0.76
BDA infrastructure	0.85	0.90	0.69
Big data analytics capabilities	**0.87**	**0.90**	**0.64**
Innovativeness	0.88	0.91	0.67
Risk-Taking	0.80	0.86	0.61
Pro-activeness	0.82	0.88	0.58
Entrepreneurial orientation	**0.80**	**0.84**	**0.64**
Market capitalizing agility	0.72	0.84	0.63
Operational adjustment agility	0.72	0.84	0.64
Organizational agility	**0.80**	**0.91**	**0.84**

Note*:* Bold used for higher-order construct values.

Table 4.13: Discriminent validity Fornell-Larcker and correlation coefficient

Construct	1	2	3	4	5	6	7	8	9	10
1 Data-Driven culture	**0.75**									
2 Organizational learning	0.64	**0.82**								
3 Technical skills	0.47	0.61	**0.83**							
4 Management skills	0.49	0.49	0.76	**0.87**						
5 BDA infrastructure	0.34	0.36	0.73	0.53	**0.83**					
6 Innovativeness	0.36	0.34	0.67	0.66	0.51	**0.82**				
7 Risk-Taking	0.12	0.18	0.25	0.33	0.29	0.23	**0.78**			
8 Pro-activeness	0.25	0.23	0.59	0.52	0.57	0.76	0.32	**0.76**		
9 Market capitalizing agility	0.22	0.28	0.41	0.51	0.31	0.56	0.27	0.55	**0.79**	
10 Operational adjustment agility	0.23	0.33	0.47	0.55	0.32	0.65	0.18	0.48	0.67	**0.80**

Note: Diagonal bold values represent the square root of the AVE, while the off-diagonals represent the correlations.

Table 4.14: Discriminent validity using Heterotrait-Monotrait (HTMT) test.

Construct	1	2	3
1 Big data analytics capability			
2 Entrepreneurial orientation	0.80		
3 Organizational agility	0.60	0.82	

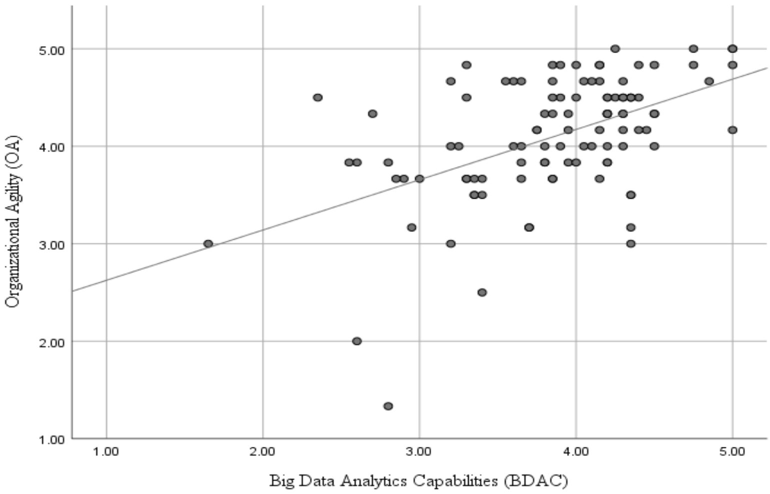

Figure 4.12: Organizational Agility by Big Data Analytics Capability

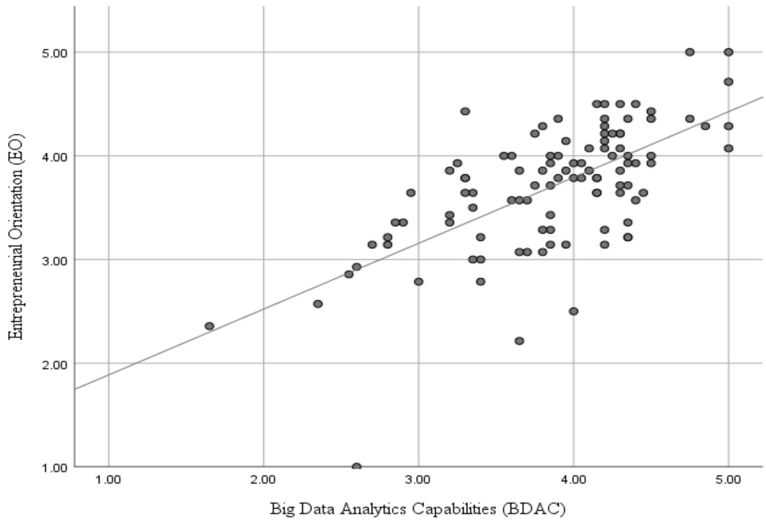

Figure 4.13: Entrepreneurial Orientation by Big Data Analytics Capability

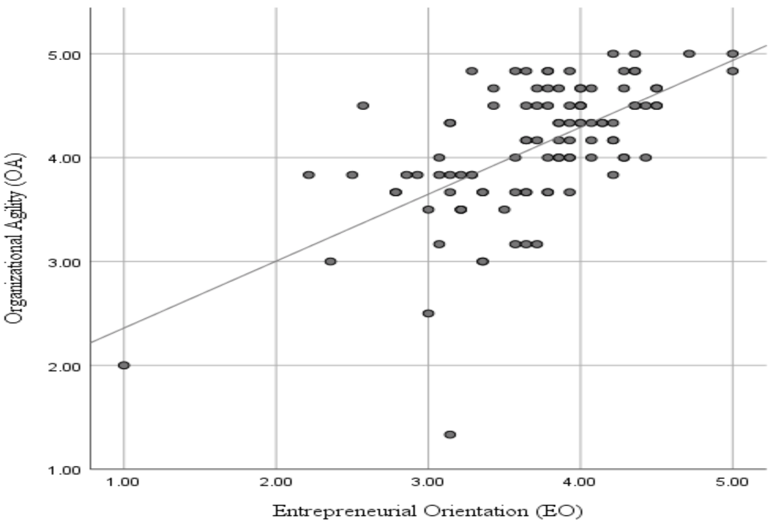

Figure 4.14: Organizational Agility by Entrepreneurial Orientation

4.5 Structural Model Analysis

To validate the hypotheses, we assessed the structural model using the empirical data. Our assessment of the structural model included examining the variance inflation factors (VIF), the path coefficients for the relationships in our model, variance explained (R2) of dependent variables, effect size of predictors variables (f2), and Stone-Geisser's (Q2) for endogenous. The VIF statistic has been used to assess collinearity among predictors constructs. The VIF values listed in Table 4.15 do not surpass the cut-off point (VIF<5) (Becker et al., 2015; Joseph F Hair et al., 2006; Mason & Perreault Jr, 1991), which indicates that collinearity is not an issue in the present study.

Bootstrapping with 5000 resamples was used to test the level of significance of the path coefficients in the model (Dubey et al., 2019; Henseler et al., 2009; Peng & Lai, 2012) was conducted to boost the level of estimation accuracy. Table 4.16 depicts the PLS path coefficients and their attached p-values. Although there are significant total effects of big data analytics on organizational agility ($\beta = 0.51$; $p < 0.001$), the direct path of big data analytics capabilities to organizational agility when the entrepreneurial orientation is accounted for ($\beta = 0.16$; $p > 0.05$) does not have a significant effect in our model. Hence, the hypothesis H1 was not supported. On the other hand, the paths big data analytics capabilities to entrepreneurial orientation ($\beta = 0.65$; $p < 0.001$), entrepreneurial orientation to organizational agility ($\beta = 0.54$; $p < 0.001$) are positively linked. Hence, the hypotheses H2 and H3 were supported.

The Explanatory power of the research model was examined based on explained variance (R2). The results show that 42 percent of entrepreneurial orientation is explained by our research model. Besides, the research model explained 43 percent of the variation in organizational agility.

Further, to gauge the effect size of the predictor construct (f2) we employed Cohen’s formula; the values higher than 0.02, 0.15 and 0.35 are considered small, medium, and large effect sizes (Cohen, 2013). The effect size of big data analytics capabilities on entrepreneurial orientation is 0.73, entrepreneurial orientation on organizational agility is 0.29. Then we examined the predictive relevance (Q2) to assess the model’s predictive accuracy (Geisser, 1974; Stone, 1974) using the blindfolding procedure (Rigdon, 2014b; Sarstedt et al., 2014). The results reveal that entrepreneurial orientation (Q2 = 0.26), and organizational agility (Q2 = 0.34). All Q2 values were above cut-off point (Q2>0), providing sufficient level of predictive relevance (Joseph F. Hair et al., 2019; Peng & Lai, 2012). Figure 4.12 depicts the summary of the structural model assessment results.

Table 4.15: VIF collinearity assessment

Construct	1	2	3
1 Big data analytics capability		1	1.82
2 Entrepreneurial orientation			1.78
3 Organizational agility			

Table 4.16: Path metrics and hypotheses results

Hypothesis	Path coefficient (β)	t-value	p-value	Result
H1: BDAC → OA	0.16	1.43	0.160	Not supported
H2: BDAC → EO	0.65	11.34	0.000	Supported
H3: EO → OA	0.54	4.93	0.000	Supported

Note: BDAC= Big data analytics capabilities; EO= Entrepreneurial orientation; OA= Organizational agility.

4.5.1 Mediating Role of Entrepreneurial Orientation

The analyses of the present study point out evidence for mediating effect. The mediator is defined as a third variable plays an intermediary role in the relationship between an exogenous and endogenous variable (Rigdon et al., 2010). We used the bootstrapping technique (Hair Jr et al., 2016; Preacher & Hayes, 2008) to estimate the mediation effect.

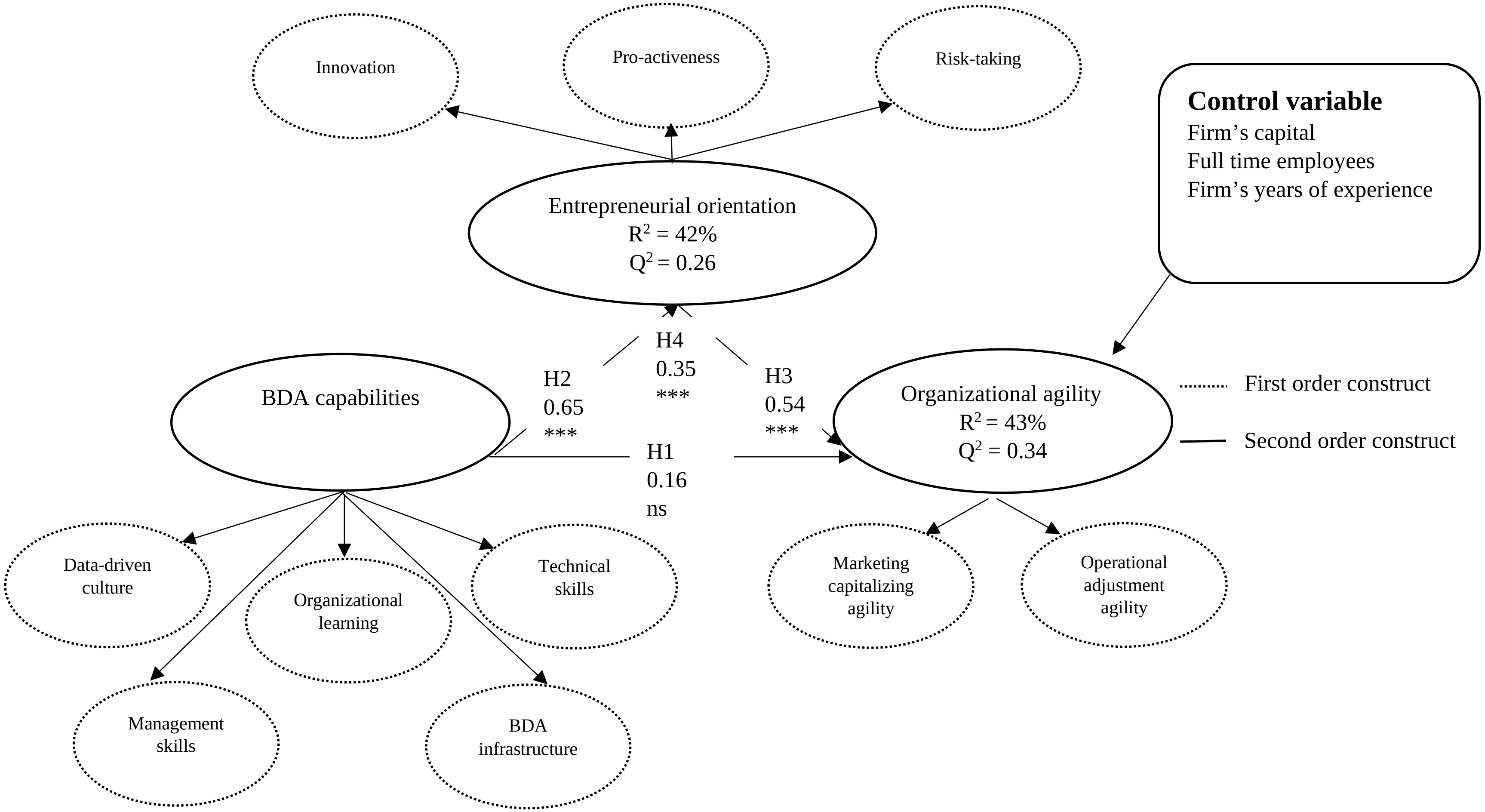

Figure 4.15: Estimated SEM

ns= non-significant; * |t| ≥ 1.96 at p = 0.05; ** |t| ≥ 2.57 at p = 0.01 level; *** |t| ≥ 3.29 at p = 0.00

Table 4.17 presents the mediation results; since the direct effect of big data analytics capabilities on organizational agility is statistically non-significant while the mediating path is significant. We can assert that entrepreneurial orientation fully mediates the relationship between big data analytics capabilities and organizational agility. Thus, H4 is supported.

Table 4.17: Mediation analysis

Hypothesis	Path coefficient (β)	t-value	p-value	Result
H4: BDAC→EO → OA	0.35	4.11	0.000	Supported (Full mediation)

Note: BDAC= Big data analytics capabilities; EO= Entrepreneurial orientation; OA= Organizational agility.

4.6 Common Method Variance

When data is collected from a single source through self-report measures, we need to be concerned about the issue of common method variance (CMV) or in some references called common method bias (N. P. Podsakoff, 2003). Reliability and validity of the constructs may be effected by a systematic error arising from the respondent bias in responding to the scales in a single questionnaire (Ashrafi et al., 2019; Malhotra et al., 2017). Tehseen, Ramayah, and Sajilan (2017) recommend using both procedural and statistical remedies to control and test common method bias. In the current research, we utilize the following procedures to reduce the effects of CMV (1) we adopt the measurement items of variables from different sources; (2) we create a psychological separation among variables using covering letter, and variables definition pane to make it clear that the measurement items of the independent and dependent variables are not related to each other; (3) the anonymity of the participants was considered; (4) we tried to keep the survey questions concise and simple.

Moreover, we have conducted a statistical method to verify that common method variance is not a major issue. Harman's one factor analysis performed to check whether a single factor represents the majority of the covariance among measures (P. M. Podsakoff et al., 2003). The output revealed that the first un-rotated factor captured only 34 percent of the variance in our data.

4.7 Post Hoc Analysis

In addition to testing the hypothesized relationships, we assessed the possible relationships of control variables (i.e. firm's years of experience, firm's capital, firm size) on organizational agility. Bootstrapping results reveals that years of experience is not significant associated with organizational agility (β = -0.02; $p>0.05$); firm's capital does not depict a significant effect on agility (β = -0.01; $p>0.05$); firm size was not related to organizational agility (β = 0.02; $p>0.05$). This indicates that firm capital, size, industry type or years of experience are not significantly related to organizational agility. Hence, we can state that expansion in our model a variety of firm characteristics (i.e. size, capital, and age) are not the reason for the variation in organizational agility, but it is due to the big data analytics capabilities and entrepreneurial orientation.

Chapter 5

RESULTS DISCUSSION, IMPLICATIONS, LIMITATIONS AND RECOMMENDATION FOR FUTURE RESEARCH

5.1 Introduction

This chapter discusses the conclusions derived from the findings of the data analyzed in the previous chapter of this study. The theoretical and managerial implications of these findings will be discussed as well. Limitations and recommendation for future research end the chapter.

5.2 Research Results

Big data with its implicit capabilities can enable business transformation and help to create competitive advantages for the business. Although many organizations have invested in their IT capabilities to boost agility levels (H. Liu et al., 2013), empirical studies have unveiled some contradicting perspectives about the influence of IT-related capabilities on firm agility (Swafford et al., 2008). Thus, there is a necessity to empirically uncover the mechanism of how investments in information systems such as big data analytics capabilities can enhance organizational agility. In this regard, we investigate the influence of big data analytics capabilities on organizational agility and also explain the role of entrepreneurial orientation as a mediating factor that facilitates this relationship.

The findings demonstrate that while big data analytics capabilities are considered a cornerstone resource for organizations, the mechanism through which it enables agility is by its role in creating an entrepreneurial orientation. These findings are consistent with the prior literature that have also demonstrated that the business gains can only be derived from the meaningful use of technologies, rather than the technologies themselves (Barratt & Oke, 2007; D. Q. Chen et al., 2015; Dubey et al., 2019; Ghasemaghaei et al., 2017; Srinivasan & Swink, 2018). In addition, we observe that entrepreneurial orientation plays a fundamental role in the relationship between big data analytics capabilities and organizational agility. This is in line with arguments in the literature that entrepreneurial orientation (EO) capability is the key to effective organizational management in today's uncertain environment (Canakoglu et al., 2018; Levesque & Joglekar, 2018; Sahi et al., 2019). Our model results emphasize the necessity for firms to develop an entrepreneurial outlook to be able to reap the results of big data analytics adoption in their decision-making process. Besides the contributions of established literature; the results of the current study present some interesting implications for theory and managerial practices, within the fields of business management and information technology.

5.3 Theoretical Implications

In the theoretical facet, the outcomes of this study contribute to extend the resource-based view framework (RBV) and its extensions, dynamic capability theory (DCT) based view and knowledge-based view (KBV). Precisely, first, the majority of previous empirical studies have analyzed the relationship between big data analytics and firm performance. This study is among the limited number of empirical studies that address the direct and indirect effects of big data analytics capabilities (BDAC) on organizational agility (OA) as an antecedent of firm competitive advantage.

Second, the prior literature has debated the relationship between BDAC, EO, and OA separately. As far as we knew, our study is one of the first studies developed a holistic model to assess the connections between these constructs. Third, during the analysis procedures we validated the Arabic version of the constructs and sub-constructs using discriminant and convergent validity tests; as such, practitioners and academics can adopt them for future projects in Jordan or even other countries. Fourth, Côrte-Real et al. (2017) reports that studies that have demonstrated potential payoffs of big data have focused on developed countries. Present study advance BDAC research by assessing its outcomes in Jordan as an example of a developing country.

5.4 Managerial Implications

In parallel to theoretical contributions, this study offers valuable managerial implications for decision-makers to maintain and improve agility by efficiently exploiting big data analytics capabilities through realized innovative, proactive, and risk-taking entrepreneurial orientation. First, despite the surge in developments in big data technology during the last ten years (Rialti et al., 2018; Sivarajah et al., 2017), top management have some concerns to invest in data-driven insights due the lack of related knowledge, the cost of implementation, and the ambiguity around the benefits in short-term, our findings present the proof that decisions with which relies on big data analytics can indeed entail profitable organizational returns (agility) if accompanied with a propensity toward innovation, pro-activeness, and risk-taking. Second, relying on the analysis results of the measurement model, executives and consultants involved in digital data and real-time analytics and strategy development can identify the influencing components of big data analytics capabilities and entrepreneurial orientation to develop business agility.

Third, our results denote that 42 percent of entrepreneurial orientation (EO) can be explained by the possess of big data analytics capabilities. Thus, managers should keep their eye on the developments of IT-related technology (Big data) to enhance the EO, which responsible for the mechanism of generating, orchestrating, and utilizing the required resources and capabilities to sense, analyze, and respond to business opportunities and threats in real time. Furth, Wiklund and Shepherd (2005); Tahmasebifard et al (2017) uncovered that organizations that have a degree of entrepreneurial orientation in their organizational processes are able to overcome environmental uncertainty. In simple words, decision-makers should have entrepreneurial capabilities (i.e. innovation, proactiveness, risk-taking) to be more agile in their decisions to achieve a company vision and objectives even in a rapidly changing environment.

5.5 Limitations and Recommendation for Further Research

Despite the favorable implications of this study, there are some limitations that can serve opportunities for improvement for future research. We have categorized these limitations into three main categories as the following: (1) Data collection- the current study assesses the constructs of the research based on top management perceptions, the reason behind that is top managers have a comprehensive knowledge of a firm's resources and its strategic issues. The data collected are the result of one response per firm over a specific period of time. This approach of data collection could involve in a risk of common method bias. Common method bias assessment test was conducted, thus revealing that their method bias is not likely. However, future studies can include multiple sources of data to further mitigate the chance of this bias. Moreover, longitudinal study can be performed to explore the impacts of big data analytics capabilities on organizational agility over a long period of time.

(2) Scope- our article examines the connection between BDAC and OA at the organization level. furthermore, our data set reflect the responses of manufacturing firms among Jordan. For future studies researchers might focus on service sector within the scope of business unit or departmental level, which may establish new business insights into the capabilities of big data analytics. (3) Research approach- this study follows a quantitative approach to explain the value of BDAC. The outcome demonstrates that organizational process (entrepreneurial orientation) enables the effects stem from BDAC. Future research could use a hybrid approach (quantitative with qualitative) by integrating different ways of knowing to improve understanding of the findings.

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APPENDICES

Appendix A: Ethical Approval Letter

Doğu Akdeniz Üniversitesi
"Erdem, Bilgi, Gelişim"

Eastern Mediterranean University
"Virtue, Knowledge, Advancement"

99628, Gazimağusa, KUZEY KIBRIS /
Famagusta, North Cyprus,
via Mersin-10 TURKEY
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Etik Kurulu / *Ethics Committee*

Reference No: ETK00-2020-0230 16.11.2020

Subject: Your application for ethical approval.

Re: Osama Musa Ali Al-Darras
Faculty of Business & Economics.

EMU's Scientific Research and Publication Ethics Board (BAYEK) has approved the decision of the Ethics Board of Business & Economics (date: 12.11.2020, issue: 2020/10) granting Osama Musa Ali Al-Darras from the Faculty of Business & Economics to pursue with his/her PhD thesis work titled **"Big Data Analytics Capabilities and Organizational Agility"** supervised by Prof. Dr. Cem Tanova.

Prof. Dr. Yücel Vural
Chair, Board of Scientific Research and Publication Ethics - EMU

YV/ns.

www.emu.edu.tr

Appendix B: Research Questionnaire

	Business Administration Department **Faculty of Business and Economics** **Eastern Mediterranean University** **Famagusta, Turkish Republic of Northern Cyprus** **Tel: +90 392 630 1281 Fax: +90 392 365 1017** **Web: https://fbe.emu.edu.tr**

Questionnaire

Dear Participant,

In partial fulfillment of the requirements for the degree of Ph.D. in Business Administration the researcher intends to conduct a study on **Big data analytics capabilities and organizational agility in the manufacturing sector**. This survey questionnaire has been developed based on the relevant academic literature and is divided into four main sections:

1. Firm characteristics
2. Big data analytics capabilities
3. Entrepreneurial orientation dimensions
4. Organizational agility

Your participation is voluntary and you are not obliged to participate in this research and are free to refuse to participate. You may also withdraw from the study at any point without giving any reason. All answers are anonymous and will be for scientific research only. Your participation is valuable to us. By participating, you will be helping researchers understand the role that big data and information management plays in manufacturing firms.

Thank you, we highly appreciate your time and effort.

Researcher (Student)	**Supervisor**
Osama Musa AL-Darras Eastern Mediterranean University Department: Business Administration E-Mail: darras.osama@gmail.com Tel: +962 795 582 743	Prof. Dr. Cem Tanova Eastern Mediterranean University Department: Business Administration E-Mail: cem.tanova@emu.edu.tr Tel: +90 392 630 1403/3201

Instructions: Please respond to the following statements by checking the appropriate box or entering the appropriate number according to what is applicable to your Organization.

Section A: Firm Characteristics

How many years has the firm been operating? **عدد سنوات عمل الشركة**	

firm's capital (in Jordanian dinar) **رأس مال الشركة** **(بالدينار الاردني)**	

How many full-time employees are in the firm? **عدد العاملين الدائمين لدى الشركة**	

Industry sub-sector **قطاع الصناعة الفرعي**	**Garments & Leather** **الجلود والمحيكات**	☐
	Pharmaceuticals & Medical Supplies **الصناعات العلاجية واللوازم الطبية**	☐
	Chemicals & Cosmetics **الكيماوية ومستحضرات التجميل**	☐
	Plastics & Rubber **الصناعات البلاستيكية والمطاطية**	☐
	Engineering & Electronics **الهندسية والكهربائية**	☐
	Wood & Furniture **الخشبية والأثاث**	☐
	Construction **الإنشائية**	☐
	Agri-Business & Agro-Processing **التموينية والغذائية والزراعية والثروة الحيوانية**	☐
	Packaging & Paper **التعبئة والتغليف والورق والكرتون واللوازم المكتبية**	☐
	Extraction **التعدين**	☐

Section B - Big data analytics capabilities						
Item	**Statement**	**Strongly disagree لا اوافق بشدة**	**Disagree لا اوافق**	**Neutral محايد**	**Agree موافق**	**Strongly agree اوافق بشدة**
		1	**2**	**3**	**4**	**5**
Data-Driven culture (DDC): The behavior of decision-making based on insights extracted from data analysis results. الثقافة القائمة على البيانات هي سلوك اتخاذ القرار بناءً على الرؤى المستمدة من نتائج تحليل البيانات.						
DDC1	Our firm considers data as an asset. تنظر شركتنا الى البيانات على انها اصل من اصول الشركة.	☐	☐	☐	☐	☐
DDC2	Our employees base most decisions on data rather than instinct. يعتمد موظفونا في معظم قراراتهم على البيانات وليس على الغريزة.	☐	☐	☐	☐	☐
DDC3	We regularly improve the business decision making processes in response to the insights obtained from data. نقوم بانتظام بتحسين عمليات اتخاذ قرار العمل استجابة للرؤى التي يتم الحصول عليها من البيانات.	☐	☐	☐	☐	☐
DDC4	Decision-making process based on big data analytics is part of our organizational culture. عملية صنع القرارعلى أساس تحليلات البيانات الضخمة هي جزء من ثقافتنا التنظيمية.	☐	☐	☐	☐	☐
Organizational learning (OL): The process of extending and disseminating the knowledge to those who need it to improve performance levels. التعلم التنظيمي: عملية نشر المعرفة ونشرها لمن يحتاجها لتحسين مستويات الأداء.						
OL1	Big data analytics knowledge is shared within the firm. يتم مشاركة المعرفة بتحليلات البيانات الضخمة داخل الشركة.	☐	☐	☐	☐	☐
OL2	Our employees are eager to transfer their knowledge about big data analytics. موظفونا حريصون على نقل معرفتهم حول تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐
OL3	Our employees' feedback about big data analytics are systematically reviewed. تتم مراجعة ملاحظات موظفينا حول تحليلات البيانات الضخمة بشكل منهجي.	☐	☐	☐	☐	☐
OL4	Our staff is able to acquire new big data analytics knowledge. موظفونا قادرون على اكتساب معرفة جديدة من خلال تحليل البيانات الضخمة	☐	☐	☐	☐	☐

Item	Statement	Strongly disagree لا اوافق بشدة	Disagree لا اوافق	Neutral محايد	Agree موافق	Strongly agree اوافق بشدة
		1	**2**	**3**	**4**	**5**
Technical skills (TS): The competence to use new technological tools or algorithms to draw readable information from large dataset. المهارات التقنية هي الكفاءة في استخدام أدوات تكنولوجية جديدة أو خوارزميات جديدة لاستخلاص معلومات مقروءة من مجموعة بيانات كبيرة.						
TS1	We invest in the latest technologies of big data analytics. نحن نستثمر في أحدث تقنيات تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐
TS2	Our firm hires high-skilled people on big data analytics. تقوم شركتنا بتوظيف أشخاص ذوي مهارات عالية في تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐
TS3	Our firm provides training to improve the technical skills of employees. توفر شركتنا التدريب لتحسين المهارات التقنية للموظفين.	☐	☐	☐	☐	☐
TS4	The technical skills owned by our own employees assist to accomplish their jobs effectively. المهارات التقنية التي يملكها موظفونا تساعد على إنجاز وظائفهم بشكل فعال.	☐	☐	☐	☐	☐
Management skills (MGS) Practice of planning, implementation and evaluation of data-related process and resources, and understanding how the output extracted from big data can be applied to different functional areas in the organization. مهارات الإدارة هي ممارسة تخطيط وتنفيذ وتقييم العمليات والموارد المتعلقة بالبيانات ، وفهم كيفية تطبيق المخرجات المستخرجة من البيانات الضخمة على مجالات وظيفية مختلفة في المنظمة.						
MGS1	Our managers can evaluate the outcomes of big data analytics to accelerate decision-making. يستطيع مديرينا تقييم نتائج تحليلات البيانات الكبيرة لتسريع عملية صنع القرار.	☐	☐	☐	☐	☐
MGS2	Our managers have a good sense of where to implement big data analytics. يمتلك مديرينا فكرة جيدة عن مكان تنفيذ تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐
MGS3	Managers in our firm have an ability to evaluate the returns extracted from big data analytics. المديرين في شركتنا لديها القدرة على تقييم مخرجات تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐
MGS4	Our managers are able to anticipate the future business needs through big data analytics output. مديرينا قادرون على توقع احتياجات العمل المستقبلية من خلال مخرجات تحليلات البيانات الضخمة.	☐	☐	☐	☐	☐

No.	Statement	Strongly disagree لا اوافق بشدة	Disagree لااوافق	Neutral محايد	Agree موافق	Strongly agree اوافق بشدة
		1	**2**	**3**	**4**	**5**
Big data analytics infrastructure (BDAI): Ability of the big data analytics ingredients such as software, hardware, data, and networks to enable the big data team to quickly response to changes in system components of a firm. البنية التحتية لتحليلات البيانات الضخمة: قدرة مكونات تحليلات البيانات الضخمة مثل البرامج والأجهزة والبيانات والشبكات لتمكين فريق البيانات الضخمة من الاستجابة بسرعة للتغيرات في مكونات نظام الشركة.						
BDAI1	Our firm is in the process of implementing or implemented different data visualization tools. شركتنا بصدد استخدام/ استخدمت ادوات مختلفة لتمثيل البيانات.	☐	☐	☐	☐	☐
BDAI2	We are in the process of implementing or implemented data driven sensors. نحن بصدد استخدام /استخدمنا أجهزة استشعار تعتمد على البيانات.	☐	☐	☐	☐	☐
BDAI3	We have flexible data management infrastructure (e.g. software, hardware, data, and networks). نملك بنية تحتية مرنة لإدارة البيانات (مثل البرامج والأجهزة والبيانات والشبكات).	☐	☐	☐	☐	☐
BDAI4	Our firm has explored or adopted cloud-computing services for performing analytics. قامت شركتنا باعتماد خدمات الحوسبة السحابية لإجراء التحليلات.	☐	☐	☐	☐	☐

Section C - Entrepreneurial orientation dimensions						
No.	**Statement**	**Strongly disagree لا اوافق بشدة**	**Disagree لا اوافق**	**Neutral محايد**	**Agree موافق**	**Strongly agree اوافق بشدة**
		1	**2**	**3**	**4**	**5**
Innovativeness (INO): Firm's ability to find an unconventional solution for problems and creating substantial changes in their capabilities to achieve competitive advantage. الابتكار هو قدرة الشركة على إيجاد حل غير تقليدي للمشاكل وإحداث تغييرات جوهرية في قدراتها لتحقيق ميزة تنافسية.						
INO1	Our top management always promotes ideas of novel products for markets. تشـــجع إدارتنا العليا دائمًا على الأفكار الجديدة لمنتجات الاسواق.	☐	☐	☐	☐	☐
INO2	Our top management are very open to innovative initiatives in order to exploit opportunities in market. إدارتنا العليا منفتحة جدًا على المبادرات المبتكرة من أجل استغلال الفرص في السوق.	☐	☐	☐	☐	☐
INO3	We are willing to try unusual solutions in our functional activities. نحن على استعداد لتجربة حلول غير اعتيادية في أنشطتنا الوظيفية.	☐	☐	☐	☐	☐
INO4	Our top management continually seeks to raise R&D budget. تسعى إدارتنا العليا باستمرار إلى رفع ميزانية البحث والتطوير.	☐	☐	☐	☐	☐
INO5	When it comes to problem-solving, we support creative solutions more than conventional solutions. عندما يتعلق الأمر بحل المشكلات ، فإننا ندعم الحلول الإبداعية أكثر من الحلول التقليدية.	☐	☐	☐	☐	☐
Pro-activeness (PROA): Firm's conduct toward expecting future needs of markets and the changes in the business environment before competitors. النشاط الاستباقي هو سلوك الشركة تجاه توقع الاحتياجات المستقبلية للأسواق والتغيرات في بيئة الأعمال قبل المنافسين.						
PROA1	In dealing with our competitors, we typically initiate actions competitors respond to. عند التعامل مع منافسينا ، نبدأ عادةً في اتخاذ إجراءات يستجيب لها المنافسون.	☐	☐	☐	☐	☐
PROA2	We have a passion to introduce novel ideas or products prior to rivals. لدينا شغف لتقديم أفكار أو منتجات جديدة قبل المنافسين.	☐	☐	☐	☐	☐

No.	Statement	Strongly disagree لا اوافق بشدة	Disagree لا اوافق	Neutral محايد	Agree موافق	Strongly agree اوافق بشدة
		1	2	3	4	5
PROA3	We are often the first firm to introduce new operating technologies. غالبًا ما نكون أول شركة تقدم تقنيات تشغيل جديدة.	☐	☐	☐	☐	☐
PROA4	We are usually anticipating the future business environment changes. عادة ما نتوقع تغييرات بيئة الأعمال المستقبلية.	☐	☐	☐	☐	☐
PROA5	Our firm prioritizes to invest on new projects rather than sitting and waiting for someone else to do. تعطي شركتنا الأولوية للاستثمار في مشاريع جديدة بدلاً من الجلوس وانتظار قيام شخص آخر بذلك.	☐	☐	☐	☐	☐
Risk-Taking (RISK): The firm bold actions to invest in opportunities available in the business environment. المخاطرة هي إجراءات الشركة الجريئة للاستثمار في الفرص المتاحة في بيئة الأعمال.						
RISK1	Our firm has a strong preference for risky projects. تملك شركتنا نزعة قوية اتجاه المشاريع الخطرة.	☐	☐	☐	☐	☐
RISK2	we believe that bold actions are necessary to achieve the firm's objectives. نعتقد أن الإجراءات الجريئة ضرورية لتحقيق أهداف الشركة.	☐	☐	☐	☐	☐
RISK3	We accept taking out bold action by نقبل القيام venturing into the unknown. بعمل جريء من خلال المغامرة في المجهول.	☐	☐	☐	☐	☐
RISK4	Our firm tends to act boldly in situations where risk is involved. تميل شركتنا إلى التصرف بجرأة في المواقف التي تنطوي على مخاطر.	☐	☐	☐	☐	☐

Item	Statement	Strongly disagree لا اوافق بشد	Disagree لا اوافق	Neutral محايد	Agree موافق	Strongly agree اوافق بشدة
		1	**2**	**3**	**4**	**5**
Section D – Organizational agility						
Market capitalizing agility (MCA): The ability to quickly respond to the target market's need by constant monitoring of the available opportunities and rapidly developing products and/or services to satisfy customer desires. مرونة السوق هي القدرة على الاستجابة بسرعة لاحتياجات السوق المستهدفة من خلال المراقبة المستمرة للفرص المتاحة وتطوير المنتجات و / أو الخدمات بسرعة لتلبية رغبات العملاء.						
MCA1	Our firm deals with market-related chaos as opportunities to capitalize on them rapidly. تتعامل شركتنا مع حالة الفوضى المتعلقة بالسوق كفرص للاستفادة منها بسرعة.	☐	☐	☐	☐	☐
MCA2	We are quick to apply appropriate decisions in the face of market/customer changes. نتخذ القرارات المناسبة في مواجهة تغييرات السوق / العملاء بشكل سريع.	☐	☐	☐	☐	☐
MCA3	our firm permanently looks for ways to reinvent/re engineer its business to better serve our target market. تبحث شركتنا بشكل دائم عن طرق لإعادة اختراع / إعادة هندسة أعمالها لخدمة سوقنا المستهدف بشكل أفضل.	☐	☐	☐	☐	☐
Operational adjustment agility (OAA): The firm's internal business operation ability to rapidly identify market demands and turn it into competitive action. سرعة التكيف التشغيلي هي قدرة العمليات التجارية الداخلية للشركة على تحديد متطلبات السوق بسرعة وتحويلها إلى عمل تنافسي.						
OAA1	Whenever there is a disruption in supply chain from our suppliers, we can quickly adopt alternative internal adjustments. يمكننا اعتماد تعديلات داخلية بديلة كلما حدث خلل في سلسلة التوريد من موردينا بسرعة.	☐	☐	☐	☐	☐
OAA2	Our firm can quickly scale up or down production/ service levels to support fluctuations in the market demand. يمكن لشركتنا زيادة أو خفض مستويات الإنتاج / الخدمة بسرعة لدعم التقلبات في طلب السوق.	☐	☐	☐	☐	☐
OAA3	We rapidly fulfill demands of our customers; our customers have confidence in our ability. نلبي طلبات عملائنا بسرعة ؛ عملاؤنا يثقون في قدرتنا.	☐	☐	☐	☐	☐

Appendix C: Loading of the Indicator Variables.

loading of the indicator variables.

Construct	Item	Loading
Big data analytics capabilities		
	DDC1	0.70
	DDC2	0.78
	DDC3	0.75
	DDC4	0.77
	OL1	0.79
	OL2	0.81
	OL3	0.84
	OL4	0.82
	TS1	0.82
	TS2	0.88
	TS3	0.86
	TS4	0.75
	MGS1	0.89
	MGS2	0.86
	MGS3	0.90
	MGS4	0.85
	BDAI1	0.85
	BDAI2	0.84
	BDAI3	0.79
	BDAI4	0.85
Entrepreneurial orientation		
	INO1	0.82
	INO2	0.87
	INO3	0.77
	INO4	0.79
	INO5	0.83
	RISK1	0.78
	RISK2	0.78
	RISK3	0.80
	RISK4	0.77
	PROA1	0.76
	PROA2	0.77
	PROA3	0.81
	PROA4	0.74
	PROA5	0.74
Organizational agility		
	MCA1	0.73
	MCA2	0.86
	MCA3	0.79
	OAA1	0.79
	OAA2	0.75
	OAA3	0.85

Note: DDC= Data-Driven culture; OL= Organizational learning; TS= Technical skills; MGS= Management skills; BDAI= Big data analytics infrastructure; INO= Innovativeness; RISK= Risk-taking; PROA= Pro-activeness; MCA= Market capitalizing agility; OAA= Operational adjustment agility.

Appendix D: Higher-order Loading Scores.

Higher-order loading scores.

	BDAC	EO	OA
1 Data-Driven culture	0.71		
2 Organizational learning	0.76		
3 Technical skills	0.91		
4 Management skills	0.84		
5 BDA infrastructure	0.75		
6 Innovativeness		0.90	
7 Risk-Taking		0.52	
8 Pro-activeness		0.92	
9 Market capitalizing agility			0.91
10 Operational adjustment agility			0.92

Note: BDAC= Big data analytics capabilities; EO= Entrepreneurial orientation; OA= Organizational agility.