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Relationship Between Strategic Dexterity, Absorptive Capacity, and Competitive Advantage

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This is to certify that the doctoral study by

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Walden University
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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Small- and medium-sized enterprise (SME) manufacturing executives and managers are concerned with the rapid technological changes involving artificial intelligence (AI), machine learning, and big data. To compete in the global landscape, effectively managing digital and artificial intelligence changes among SME manufacturing executives and managers is critical for leaders to compete in 2023 and beyond. Grounded in the dynamic capabilities view theory, the purpose of this quantitative correlation study was to examine the relationship between strategic dexterity, absorptive capacity, and competitive advantage. The participants were 66 executives and managers of SME manufacturing organizations who use big data and analytics daily and agreed to complete the AI Analytics Survey Questionnaire using Wu et al.'s survey. The results of the multiple linear regression were significant $F(2, 63) = 54.29$, $p < .001$, $R^2 = .63$. In the final model, both predictors were significant: strategic dexterity ($t = 2.48$, $p = .02$, $ß = .391$) and absorptive capacity ($t = 2.61$, $p = .01$, $ß = .439$). A key recommendation is for SME manufacturing executives and managers to understand how to integrate, build, and orchestrate their strategic digital assets when implementing absorptive capacity strategies within their organization. The implications for positive social change include the potential to provide SME manufacturing executives and managers with an understanding of how these technologies can be integrated into the future of data analytics and automation, the support towards a digital economy, and the social effects of artificial intelligence on the underserved and underrepresented groups.

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Dedication

First and foremost, I dedicate this achievement to my beautiful wife, Anita, and my family. To my wife, Anita Monyei, your support, patience, and love positively influenced my doctoral journey and intellectual development. Your belief in me has made this doctorate journey pleasant, exciting, and thrilling. I love you so much. You have been instrumental in my doctorate journey and success in life. I thank you for sticking with me on this momentous occasion and journey of our lives. As well, my children, Sasha, Jaden, and William, thank you for believing in your dad, supporting me, and bearing with me as I pursued my doctoral study to its completion. I love you all. Despite the failures and hardships along the way (and there were many seen and unseen circumstances that could have derailed this journey), I was able to finish because of the sincere trust, time, and effort you placed in me. I will always remember this.

Thank you for supporting me.

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Section 1: Foundation of the Study

Innovation is necessary for an organization's continued relevance in the global business markets when seeking to disrupt their industry where customer needs and competitive forces exert pressure to meet critical success factors for sustained long-term performance, growth, and competitive advantage (CA). Business executives and managers continue to face difficulties related to rapid technological growth (Milan et al., 2020), which requires data amalgamation of strategic dexterity (SD), absorptive capacity (AC), and CA in the United States. Atkinson et al. (2020) argued that critical market knowledge shifts an organization's strategies towards using data as an asset, learning from successes and failures of multidisciplinary firms that enable achievable CA. More manufacturing executives and managers with small- and medium-sized enterprises (SMEs) acknowledge the importance of data as a sustainable CA and information technology (IT)-enabled dynamic capability in a fast-paced business environment as necessary to reap economic benefits (Mikalef et al., 2020; Zaki et al., 2019). For this reason, digital skills, big data (BD) asset management, and new IT development lead to business competitive growth that keeps up with the stakeholder demands through a renewed focus on human capital, investment alignment, and IT and data resources over time. The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA.

Background of the Problem

CA is the integration and synchronization of resources, human capital, investments, research and development (R&D), and BD that gives the organization an edge over competitive forces in the global marketplace. Manufacturing SMEs must use SD, finite resources, and highly specialized expertise to transform their organization through applying BD to varying individual and business entities as a CA. With the introduction of BD, organizational leaders have relied heavily on IT that can deliver value to consumers at unparalleled speed and innovation (both as an external and internal advantage for the organization), where IT becomes a strategic resource for companies willing to distinguish their brands from other competitors (Carr, 2003; Kozielski & Sarna, 2020; Negulescu, 2019; Uden & Del Vecchio, 2018). Stalk (1998) stated that CA is a time-spectrum dependent on the following scale-based strategies: (a) low labor costs, (b) high-quality materials, and (c) just-in-time inventories. Companies must dictate their flexible IT strategies to reduce their market risk exposure while rewarding their workforce, seeking early IT adaptations, and continuously shifting their market focus. Spanaki et al. (2018) explained that new value creation exists by strengthening functional divisions' asset and information operations and optimizing data integration. Zangiacomi et al. (2020) described that the digital transformation of manufacturing, pressed by rapid technological changes, resource scarcity, and globalization, will continue unless BD is part of the digital and agile solution within the manufacturing industry. The reliance of skilled executives and managers is important to execute a successive manufacturing strategy centered on human-machine teaming, digital transformation of the manufacturing landscape, and the customer-strategy alignment that supports business growth. The manufacturing industry must incorporate these transformative challenges in order to ensure failure through experimentation provides lessons-learned for iterative and continuous modeling successes, however, it must be a human-centered digital transformation that integrates the use of BD, AI, and ML to have a competitive manufacturing environment long-term.

Problem Statement

The failed integration between BD and strategic flexibility by product-oriented SMEs leads to a lack of CA (Olszak & Zurada, 2020). With the accumulated information on the internet reaching 44 zettabytes in 2020 (Desjardins, 2019), only 8% of small businesses have added BD to transform their organization (Sun et al., 2018). The general business problem was that some SME manufacturing leaders did not know how to infuse BD structurally within their enterprise, resulting in a competitive disadvantage. The specific business problem was that some SME manufacturing senior executives and managers did not know whether a relationship existed between SD, AC, and CA.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA. The independent variables were SD and AC, while the dependent variable was CA. The target population for the study were SME manufacturing senior executives and managers in the United States. The implications for positive social change include enhancing employee productivity in data usage and advocating for sustainability efforts within underserved and underrepresented communities towards a digital economy.

Nature of the Study

I selected a quantitative methodology for this study. Using a quantitative approach enables a researcher to explain the degree of causality based on statistical significance testing (McCusker & Gunaydin, 2015). The quantitative method was appropriate for this study because I planned to conduct a holistic analysis of a phenomenon observed in time through measurable data to create new insights into previously held theories. The qualitative method is appropriate when researchers discuss individuals' viewpoints using descriptive texts, not numerical data (Vaismoradi et al., 2016). The mixed method is appropriate when researchers combine quantitative and qualitative approaches as a hybrid bridge for more in-depth analysis (Harrison, 2013). The qualitative method and mixed method were inappropriate for this study because the descriptive context of data collection and theory development use inductive reasoning.

I selected a correlational design for this study. Using the correlational design, a researcher measures the statistical linearity among variables (Seeram, 2019). The correlational design was appropriate for this study because it provides a statistical estimate of the relationship between a set of predictor variables and a dependent variable. The quasi-experimental design establishes a control causality without the assignment of random numbers (Head & Harsin, 2018). The causal-comparative design is used when seeking to discover a causative relationship involving at least one categorical variable (Fulmer, 2018). The quasi-experimental and causal-comparative designs were inappropriate for this study because there were no random assignments of SME manufacturing leaders to specific groups or attempts to explain the known cause of the variables' differences.

Research Question and Hypotheses

RQ: What is the relationship between SD, AC, and CA?

H_0: There is no statistically significant relationship between SD, AC, and CA.

H_1: There is a statistically significant relationship between SD, AC, and CA.

Theoretical Framework

Teece et al. (1997) developed the dynamic capabilities view (DCV) theory through using the views of economic competition (Schumpeter, 1934), organizational resource value (Penrose, 1959), resource combination (Rubin, 1973), and routine behaviors and capabilities (Nelson & Winter, 1982). Teece et al. described the DCV theory as an improvement to the static nature of the resource-based view (RBV) theory. Teece et al. identified the following key constructs underlying the theory: (a) SD, (b) AC, and (c) CA. As applied to this study, the DCV theory holds that I could expect the independent variables (i.e., dynamic capabilities constructs), measured by the Big Data Analysis Adaptation Questionnaire (Shan et al., 2019), to predict the dependent variable of CA because organizations are forced to compete at a dynamic pace while establishing unique capabilities in BD towards sustainable CA.

Operational Definitions

Operational definitions refer to the clarification of terminology that allows for the critical operationalization found in the nexus between meanings, concepts, and assumptions (Slife et al., 2016). Operational definitions require researchers to fundamentally understand their selected construct variables' operational terms, the convergence of empirical outcomes, and scholarly definition through existing research (Peña et al., 2018). The operational definition demonstrates how to interpret the verbiage, distinctive scholarly opinions, and technical terms that I refer to in the research study.

BD: The structured and unstructured sources of diverse information encompassed in the form of its volume, variety, value, veracity, and velocity that shows the scale of data found in nature (Grover et al., 2018).

Assumptions, Limitations, and Delimitations

A researcher assesses the effects of their assumptions, limitations, and delimitations by addressing readers' fundamental skepticism about the credibility and trustworthiness of the research (T. J. Ellis & Levy, 2009). An unperceptive and inadequate approach to external incidences can affects the reader's confidence in a study and allow for weaknesses and shortcomings through data misinterpretation, bias methodology, and split perceptual familiarity (Barnham, 2015). Bounding the research by a set of core limiters is done to identify and relieve the audience from any distractions through interwoven elements that seek to ensure the dependability and assurances of the study.

Assumptions

Assumptions are an individual's perceptions and misunderstandings about the nature of the facts through presumptions (Gelo et al., 2008; Lau & Chiu, 2001). When a researcher can address the subject as an acceptance of truth without factual proof of evidence, it presents their belief system, diffused meaning, and abnormal conventions (T.

J. Ellis & Levy, 2009). I made three assumptions in this study. The first assumption was that each participant answered every survey question accurately, justly, and honorably. Another assumption was that participants understood the data collection questions posed to them with ease, largely because of their formal information and communication technologies (ICTs) background, expertise, and experiences. My assumption was that each company used machine learning to make informed executive and managerial decisions within their data adaptation processes.

Limitations

Within a study, the researcher presents the limits, problems, and issues that may have influenced the data interpretation as the limitations (T. J. Ellis & Levy, 2009). The researcher does not control the self-imposed factual tempo or the restricted stylistic dynamics found within the research; this includes the statistical model limits, research design selection, and geographic location confines (Theofanidis & Fountouki, 2018). I identified four limitations of this study. The first limitation was my inexperience as a researcher in completing a study. The second limitation was that the data collection questions may not have accounted for all SMEs’ attitudes or judgments regarding ICTs. The third limitation was that I had a time constraint to collect the data for the study, including accessibility issues because of an online disruption of the survey. The final limitation was in the geographic selection of SME executives and managers within the specific industry of manufacturing using machine learning in the United States.

Delimitations

Delimitations refer to acknowledged elements of the study bounded by the researcher into manageable constructs, which affect the broad inference and external validity of the research (T. J. Ellis & Levy, 2009). Unlike limitations, a researcher controls the research scope, determining what to include and exclude in the doctoral study (McGregor, 2018). This study had five delimitations. The first delimitation related to the study population, where the focus was bounded only to U.S. executives and managers in the manufacturing sector. The second delimitation was that the data collection survey was in English, constraining participants to whom English was not their primary language when contextualizing the survey. The third delimitation was that many multiplicities have their own forms of CA that exists in varying constructs, but I focused only on SD and AC for this study. Excluding all manufacturing executives and managers who operated in United States outside of the data survey period was the fourth delimitation. The fifth delimitation was my focus on U.S. manufacturing executives and managers who were grounded on current technology growth, not those leaders who adopted emerging technologies.

Significance of the Study

This study could be valuable to business practice because the findings may be used by SMEs seeking to better understand how data can be employed as a strategic asset in the company and how machine learning can create insights, knowledge, and expertise for the organization’s employees. The implications for positive social change include the potential to provide strategies that SME manufacturing senior executives and managers can use to enhance employee productivity in data utilization and digital training.

Contribution to Business Practice

The rate of technological change outpaced SMEs' participation in a market that accounts for 43.5% of manufacturing businesses with 250 or more employees (U.S. Bureau of Labor Statistics, 2019). According to Čiutienė and Thattakath (2014), an organization's dynamic capabilities must adapt to an ever-changing environment where disruptive innovation takes root as a foundation. SMEs may integrate BD while pursuing the learning technologies necessary to advance data transformation strategies.

Implications for Social Change

The strategic capability of BD can have an adverse microeconomic and macroeconomic effect on the manufacturing industry. SME executives and managers may have an inherent unwillingness to transform their organization and employees because they lack an understanding of BD realizations, perceptions, and comprehensions along with the expenses necessary to transform the organization to a digital firm. This study's results contribute to positive social change by promoting effective hiring practices for potential SME senior and midlevel managers, employing successful SME business strategies, and creating opportunities for underserved populations.

A Review of the Professional and Academic Literature

This professional and academic literature review includes a synthesis of the specified theoretical framework along with a comprehensive review of current manufacturing digitalization strategies. I begin the review with a discussion of the literature search strategy. Next, I restate the purpose and hypotheses of this quantitative correctional study in relation to the literature to contextualize the organizational structure of the literature review. Detailed explanations of the DCV theory posited by Teece et al. (1997) and its opposing theories is provided through synthesizing previous empirical studies conducted by business scholars. After exploring the literature related to DCV, I discuss the study's independent variables (i.e., SD and AC) and the dependent variable (i.e., CA) in the context of SME manufacturing organizations, their subconstructs, BD, AI, and ML.

Literature Search Strategy

My approach to the literature search strategy ensured a comprehensive and overarching review of all sources. I used the following key terms in my search: *relational embeddedness, learning orientation, absorptive capacity, competitive advantage, small and medium-sized enterprises, big data, strategic dexterity,* and *dynamic capabilities view theory*. I searched the following databases accessible through the Walden University library that had full-text availability: Business Source Complete, ScienceDirect, IEEE Xplore Digital Library, and Emerald Insight. My search parameters were limited to resources published between 2019–2023. *Ulrich's Periodical Dictionary* helped validate that 61.8% of the materials included in the literature review were from peer-reviewed journals (see Table 1).

Table 1

Literature Review Source Content

Literature review content	No. of sources 2018 and earlier	No. of sources 2019–2023	% of total peer-reviewed sources from 2019–2023
Peer-reviewed journals	89	202	61.8%
Books	8	4	0.33%
Conference materials	0	11	3.36%
Other	5	10	3.06%
Total	102	227	68.6%

Literature Organization to the Applied Business Problem

The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA. The hypotheses developed for this study are the null and alternative propositions detailed, respectively, as (a) there is no relationship between SD, AC, and CA, and (b) there is a relationship between SD, AC, and CA. To determine the difference between the null and alternate hypotheses, in-depth scrutiny was required that could allow SME manufacturing leaders to understand how their current business problems tie to possible solutions in utilizing strategic management, resource capacities, and competitive technologies to operate regardless of the uncertainty in the global environment.

In the following subsections, I first discuss the theoretical framework of the DCV theory that underpinned this research and describe the contrasting theories. Then, the importance of SMEs, including the vital contribution of the manufacturing sector and its strategic agility that leads to competitive growth, is highlighted. Finally, I discuss SD, AC, and CA as they apply to SMEs and aggregate information on the variables to define how CA infused with BD supports resource allocations to meet high consumer demands. The population comprised of SME manufacturing senior executives and managers in the United States. This study's implications for positive social change include supporting the CA, economic, and performance enhancement of manufacturing organizations to thrive in dissolute areas of the country that are suffering a digital manufacturing shock within once-established and thriving communities.

Theoretical Framework

In this literature review, I discuss the importance of Teece et al.'s (1997) DCV theory that was used as the theoretical framework in this study. Throughout the discussion, I examine the independent variables of the theory as they related to the formation of this study. Teece et al.'s theoretical concepts and the correlated dependencies of the construct variables related to manufacturing SMEs are also described. Then, I consider contrasting theories of the DCV theory, including both RBV theory and knowledge-based view (KBV) theory, to provide a holistic review of current literature on the DCV theory.

DCV Theory

The theoretical framework for this study comprised Teece et al.'s (1997) DCV theory. The DCV theory was grounded on an integrated resource management concept started with Teece and Pisano in 1994, which was extended to include internal and external resource reconfiguration and later defined to take structural commonalities found in the changing global environment, resource capacities, and knowledge acquisition for high-competitive markets (Eisenhardt & Martin, 2000; Singh & Singh, 2019; Teece et al., 1997). The DCV theory is used to consider a company's aptitude to discover, integrate, transform, and reinvent itself using the combination of both internal resources (i.e., core competencies) and external resources (i.e., AC) towards achieving a competitive advantage in a volatile, uncertain, complex, and ambiguous environment (Gonyora et al., 2022; Mikalef et al., 2019; Teece et al., 1997). The insights of DCV theory may help to better understand how a firm's managerial competencies, business functionalities, and strategic competitiveness allow it to use its resources effectively and maximize its output levels steadily. The dynamic nature of a firm avoids the pursuance of incoherence in its business functions by exploring, exploiting, and expanding the combination of resources and capabilities towards strategic business competitive advantage over rival businesses.

The DCV theory supports the strategic use of resources to aid business leaders in meeting critical business metrics that lead to CA. The strategic use could include resource orchestration (i.e., cloud computing), asset adaptation (via data integration), and management commitment, which help SMEs avoid conflicts internally between functional business units while pushing the boundaries of possibilities in organizational performance and opportunities (Kristoffersen et al., 2021a; Medeiros et al., 2020; Zeng et al., 2021). Executives and senior managers must have the capacity to sense and shape a firm's prospects while overcoming pressures through market exploitation and the seizure of opportunities that reflect a proactive and competitive position towards enabling innovative products and enhancing value-added services (Cao et al., 2019; Grover et al., 2018; Knudsen et al., 2021; Mikalef, Pateli, et al., 2020; Shan et al., 2019). The value of resource exploitation comes from the executive, structural, and technical teams in the organization who see value in the resource exploitation to create new products and services. For critical business metrics, it is essential to have a dynamic approach to the competition using a combination of managerial, functional, and technical capabilities to create the capital outcomes necessary to sustain a competitive digital edge.

In the expansive phase of the DCV theory, how managers and functional business units must use emerging technologies and innovative processes to mature and develop the firm's business activities for competition in a digital business environment are defined. SMEs must attain emergent technological assets (i.e., path-dependent capabilities) and sustain insightful data (i.e., future-oriented capabilities) as part of their business acumen to survive in current and future business climates (Cao et al., 2022; Nayak et al., 2019). Both management- and resource-related theories of the past helped advance the development of the DCV theory, expanding opportunities through emergent technologies that lead to business growth (Mikalef et al., 2019). Because of expansive global growth, agile organizations must develop continuous strategic processes where resource flexibility and BD capabilities match or exceed the pace of technological change in their industry to compete in an uncertain global market (Shan et al., 2019). Teece et al. (1997) stated that organizations must define their internal and external strategic capabilities that are difficult to imitate yet create different opportunities by expanding prospects to improve, augment, and enhance their strategic value. For instance, Kristoffersen et al. (2021a) stated that a strong DCV, adequate management, data implementation, and innovation realization lead to positive BD enablement. The expansive landscape of emerging technologies could require firm managerial commitments and pioneering functional units to emulate first-mover advantage within the defined industry, especially in manufacturing. The sole inclusion of the DCV theory cannot alone contribute to CA; however, it may determine the strategic direction necessary for a firm to compete with new technologies in an unpredictable business environment.

The combination of the DCV and BD as a distinctive source of an organization's strength allows interrelated functional business units to take advantage of their unique data as an asset while assessing their operational and strategic risks in attaining a competitive lead in their industry. The DCV theory contains a description of how internal and external resources shape the corporate environment through strategic learning and analytic services (i.e., advancing); respond to global environmental imperfections in business through ambidexterity, technological innovation, and adaptation (i.e., enabling); and meet the challenges and uncertainties with other internal factors, including continuity and differentiation (i.e., leveraging), resulting in sustained long-term advantage (Behl, 2022; Teece et al., 1997; Wiener et al., 2020). Singh and Singh (2019) examined how inherent organizational knowledge, along with absorptive capabilities, enabled organizations to anticipate and mitigate disruptive events and build resilience, leading to CA. Medeiros et al. (2020) explained that there are five indicators that explain the benefits and dimensions of the DCV: (a) information integration, (b) communication and collaborative analysis, (c) knowledge generation, (d) data sharing, and (e) organizational learning. Each indicator becomes a part of an organization's aptitude to use information in a transformative, experienced, and aspirational manner that enhanced CA for the company (Luis Casarotto et al., 2021a; Vidgen et al., 2017). The aggregate of the information created data that became integral for an organization to exist in a digital economy and necessary for the continued survival of the enterprise in a value-oriented, competitive global environment.

There are other components of the DCV theory that highlight the strength of this theory. Teece et al. (1997) described the DCV theory as an improvement to the static nature of the RBV theory. The advancement of the DCV theory defined the rate of change in the valuable, rare, imperfectly imitable, and imperfectly substitutable assets, resources, and capabilities found inside and outside organizations (Mikalef et al., 2019). Firms must determine the point in time when data as an asset advances their asset positions going forward in a fast-paced digital economy. Previous researchers reiterated the importance of establishing a rapid innovation cycle that accounts for the hyper-turbulent environment as a dynamic process by shifting resources dynamically, applying adaptive capabilities, and determining competitive intelligence, which delivers rapid business-cycle execution and actionable decision-making for business leaders (Medeiros & Maçada, 2022; Nan & Tanriverdi, 2017; Reis et al., 2020). Wiener et al. (2020) stated that the path dependencies of DCV and BD implementation directly impact the anticipated benefits of BD deployment in an organization. Several researchers defined the ability of an organization to marshal its internal analysis of its (tangible and intangible) assets, organizational processes, and knowledge as necessary in order to develop organizational growth strategies and create adaptive market changes (Dahle et al., 2018; Dam et al., 2019; Madhani, 2022; Quaye & Mensah, 2019). Static resource assets and capabilities served the past environments of pre- and post-industrial revolutions, where information was stagnant and only as good as its sources to advance valuable, rare, imperfectly imitable, and imperfectly substitutable assets across an organization's horizontal and vertical structure. The theoretical advancements in Teece et al.'s DCV theory demonstrated the necessity of SD and absorptive capabilities to determine CA, making this theory appropriate and fitting for this study.

Contrasting Theories

In this subsection, I discuss two theories that contrast with the DCV theory: the RBV theory and the KBV theory. Though these theories were not selected as the theoretical framework for this study, each provided varying frameworks of how data function as a foundation for an organization's resource and knowledge expenditures. There are limitations to the RBV and KBV theories, insomuch as only the DCV theory resolved long-term competitive issues associated with a sustainable CA in a volatile, uncertain, complex, and ambiguous environment. In the following subsections, I describe each contrasting theory to establish why these theories were not appropriate, and as demonstrated below, not selected for this study.

RBV Theory. Past business enterprises could not have anticipated the acceleration of information, advancements in technologies, the evolution of computing speed, and the degradation of environmental challenges to be as formidable as they are in the current, fast-paced, global market that challenges the CA of every organization. To explain the RBV theory, Barney (1991) described that the strategic nature of an organization operated on internal capabilities through which organizational identity, growth development, and inimitability competencies made the capabilities of the organization rare and unique in dealing with external market forces. The RBV theory is a well-developed theory that contains an explanation of how an organization's performance is partly due to a manager's control and allocation of resources (Kristoffersen et al., 2021a). In the RBV theory, the heterogeneity and fixity of resources within an organization, managed through functional units that create tangible and intangible assets for sustained and optimal performance, are defined (Akter et al., 2020; Al-Khatib, 2022; Gonyora et al., 2022; Mikalef et al., 2018). The RBV theory acts as a static orientation for businesses that seek to determine the strategic business value of their firm using the valuable, rare, imitable, and non-substitutable framework (Grover et al., 2018; Kristoffersen et al., 2021a; Shan et al., 2019). Although it deals with how SMEs allocate resources towards multiple tasks, the RBV theory is static, dormant, and abstract, failing to explain the strategic processes and deliberate procedures necessary to compete (Akter et al., 2020; Dubey et al., 2019; Hossain et al., 2021). Barney's RBV theory is an excellent theory to use in a static environment that depends on the firm's in-house capabilities and resources to provide systematic performance for the organization. However, the RBV theory fails to anticipate the dynamic environment of external market forces that influence how internal resources and capabilities should be developed to compete in innovative business markets properly.

When the market environment grows in uncertainty with new information or the introduction of new technology, the administrative control by a leader is necessary to understand how best to explore and exploit current resources to gain a competitive advantage, not just based on a performance-oriented market. RBV is invaluable to an organization, but it does not fully explain the intricate outputs that arrive at a competitive advantage because it fails to deal with certainty in external markets and data-rich global environments (Hossain et al., 2021; Mikalef et al., 2018). Mamonov and Triantoro (2018) explained that a deficiency of RBV is the obscurity of what constitutes an IT asset because it is a tangible asset that can be replicated within a short timeframe, resulting in a lack of competitive advantage. RBV firms do not use their internal capabilities alone with BD to attain competitive advantage because a lack of strategic processes, asset acquisition, accumulation, divestitures, and manager commitment can lead to some disastrous integration of large-scale data without understanding the dynamic environment (El-Kassar & Singh, 2019). RBV affirms its primary focus on resources as critical to business growth while accounting for the dynamic competence for new adaptive data to fuel long-term competition. In this study, Barney's RBV does not meet the adequate requirements to dictate how strategic dexterity along with adaptive capabilities will determine competitive advantage because resources cannot keep pace with the rate of change in a manufacturing and data-enriched environment, which may result in slow adaptability to the evolving and competitive business market.

KBV Theory. An institution's knowledge is vital to the continuity of operations. An organization's knowledge does not automatically translate to having a competitive advantage when dealing with other decisive mechanisms necessary for long-term organizational performance. The KBV theory refers to the knowledge held that is hard-to-replicate and its exclusive knowledge resources that influence a company's product and performance outcomes (Côrte-Real et al., 2017). KBV, a competency-based theory, relies on the knowledge value an organization brings to create unique and inimitable outputs (Côrte-Real et al., 2020). Knowledge is both a static and an active derivative of information that is an enriched asset for an organization to explore and exploit dynamically when reacting to changes within technological, human, and organizational structures (Domagala, 2019). Côrte-Real et al. (2020) explained that KBV handles data quality, impacting data-driven decision-making and organizational knowledge based on process sophistication. Institutional knowledge is a critical asset that drives stakeholder confidence and promotes business growth within an organization. An organization's derived information may help to create unique capabilities as a source of innovation, leading to long-term performance growth for the firm.

KBV creates an opportunity for a firm to treat its knowledge base as critical assets for exploration and exploitation to determine the best way. An organization can take its IT systems, knowledgeable staff, and historical data through a configuration of its current resources to implement changes in its production level based on its investments towards strategic dexterity (Côrte-Real et al., 2017). Strategic organizations utilize KBV to understand their knowledge management roles within new product development, the creation of BD analytics, market orientation, and resource allocations (Côrte-Real et al., 2017; Q. Yan, 2020). The combination of these two theories, RBV and KBV, are valuable requirements for an organization looking inward towards developing in-house strategies to compete within their industry or rein in their competitors within their location; it is inadequate to handle external market forces using its current resources

(Hossain et al., 2021). The strength of an organization rests in its brain trust of people, processes, and technical capabilities, which have the current configuration of the knowledge map to sustain the firm through the turbulent and chaotic economic period. The combination of competence-based theories alone does not yield the fruitful results of long-term strategic growth for small and medium-sized enterprises, which can lead to inefficiencies in resource allocation and declines in knowledge as a service.

Other Minor Theories Related to the Study. Though there are varying theories mentioned in my research, it is important to note their relevance to the topic as not to discount their future purpose towards employing a BD strategy. The first minor theory based on a physics theory is known as complex adaptive systems (CAS) theory. CAS theory defines how an organization changes its positive and negative interactions through mutual adaptability to help explain nonlinear causalities within a given system (Nan & Tanriverdi, 2017). Nan and Tanriverdi (2017) explained that the topic and purpose focused on the information systems (IS) strategic atmosphere, which acts as a new source of sustained competitive advantage for firms, seemed to explain firm deliberate actions within the hyper turbulence of complex business environments. Using agent-based modeling, this literature-based research looked at how business IT is a game-changer in firms providing the following organized information using the theory, CAS theory: (a) firm, (b) firm capability, (c) architectural IT innovation, (d) component IT innovation, (e) combined effect of component IT innovation, and (f) Opportunity for IT to afford competitive advantage (Nan & Tanriverdi, 2017). In this case, Nan and Tanriverdi described that IT acts as a conduit for promised success against other competitors or peers in the same industry. CAS theory is accomplished in two pathways: (a) bottom-up causal paths based on firm-level IT-based strategic actions and (b) top-down causal paths based on IT-induced hyper turbulent environment (Nan & Tanriverdi, 2017). These two pathways are seen as cross-level nonlinear causality between interacting firms and individual firms where the promises and challenges of IT create a holistic view of what is possible among firms in a hyper turbulent environment (Nan & Tanriverdi, 2017). The main conclusions do suggest that hyper turbulent environments are likely to increase in the future, where IT will play an influential long-term role. Strategic IT alignment will need to occur to better deal with new strategic multilevel perspectives of IS and IT strategies in the future under the CAS theory perspective.

Small- and Medium-Sized Enterprises

Over the last few years, SMEs have been apprehensive in BD adoption, exploration and digital evolution. The digital pace and rate of BD accelerated the current digital transformation of SMEs who seek analytic efficiency and operational effectiveness within uncertain environments (Shah, 2022). Most SMEs did not understand what to do with these structured and unstructured data. SMEs do not know how best to adopt BD as a disruptive technology into their process flows and functional business units even though reductions in production time and lifecycle development have been proven as a successful fact (Sassi Hidri et al., 2018; van den Broek & van Veenstra, 2018; Willetts et al., 2020). Because of the Coronavirus 2019 pandemic, the concept of geographic positioning declined, wherein a replacement, the digital environment, and data became necessary to sustain businesses at low cost while ensuring SMEs had the same access and opportunities to suppliers, customers, and manufacturers, enabling long-term digital competition in an ambiguous market (Shah, 2022). Though it does not guarantee success, technology is dependent on leadership's actions to leverage the innovation of data as a competitive advantage against rival firms (Pham et al., 2022). These data points will interact within the business analytic ecosystem as SMEs pivot from disparate information sources to shared collective understandings while providing keen impactful insights. SMEs can incorporate BD as a strategic asset to meet long-term objectives, resulting in a dynamic and mature analytic ecosystem.

Starting with its size, manufacturing SMEs are best positioned to take advantage of BD growth as a core strategic asset and value towards intelligence systems. The International Data Corporation, a premier global market intelligence provider, forecasted that the BD market would increase to $48.6 billion by 2019, excelling to a 23.1% growth (Grover et al., 2018). The combined insights across horizontal and vertical business lines and BD collaboration helped business leaders make prudent and transparent decisions about their vision and the direction for the organization (Ranjan & Foropon, 2021; van den Broek & van Veenstra, 2018). Advanced intelligence manufacturing requires SMEs to adopt new strategic designs and paradigm-thinking in real-time manufacturing, product lifecycle management, and cloud-based data integration to ensure operational data-driven integration in the organization (Adel, 2022; Chae & Olson, 2022; A. Wang & Gao, 2022). If an organization had the appropriate and relevant data to be absorbed through BD analytics, this is critical to delivering value, providing insights, and ensuring digital capabilities within complex business environments (El Hilali et al., 2020). Organizations seeking to remain competitive, must increase the use of data in their workflow, permitting differential business models to emerge that account for the wholistic view of their industry while providing targeted resources to ensure competitiveness in the digital economy (Somohano-Rodríguez & Madrid-Guijarro, 2022). SMEs must understand that the digital economy is rapidly innovating at a pace never acknowledged or seen before in human existence, moving from a traditional physical store to a digital e-commerce environment (Shah, 2022). The rapid pace of change involves the creation of a new digital collaborative environment. SMEs can accelerate their digital transformations by demonstrating the need for expanded digital marketplaces and continuous dependence on trusted and authoritative data for growth.

Manufacturing and other SMEs must rely on BD to adopt innovative strategies to prevail over their competitors. SMEs seeking to transition to a BD strategy must use a technology roadmap that helps to build a data science architecture centered on data-driven solutions, organizational structure, analytic tools, and BD (Kayabay et al., 2020, 2022). In the field of manufacturing, data-driven manufacturing resource selection impacts technical/functional decision design criterion, product necessity data analysis, and product-process-material-machine data analysis, all necessary to improve supply chain management, gain product manufacturing efficiencies, and sustain competitive advantage in the long term (Uz Zaman et al., 2022). An SME's supply chain activities depend on the employment of a digital strategy using BD, digitization, upstream and downstream processes, and IT to keep up with the amount of information flowing from consumer to suppliers in a highly competitive and data-driven organization (Chae &

Olson, 2022; Younis et al., 2022; Zhuang & Ye, 2022). Manufacturing SMEs value digital transformation using varying strategic models like social capital optimization, collaborative production, service-oriented processes, or smart factory to enhance productivity, measure IT and innovation readiness, and support in-depth integration of human capital to move the industry forward (L. Li et al., 2022; Xue et al., 2022; Zhuang & Ye, 2022). Silvestri (2021) analyzed that in manufacturing, the use of computational fluid dynamics along with BD and cloud systems enabled an improved system analysis using digital twins, a virtual development model to support the management of smart factories through data optimization. In manufacturing, data-driven optimization synchronized among varying functional business units, will be essential to orchestrate digital strategies at speed to keep up with the complex global environment.

Other SME industries, e-commerce, health care, and hospitality, are moving towards data-driven business models that have BD as a strategic asset, increasing productivity and innovation for organizations. Within e-commerce, SMEs realized the importance of combining social media and BD through early adoption that increased customer value, measured consumer behavior, and generated new business revenues for companies and e-vendors (Alrumiah & Hadwan, 2021; van den Broek & van Veenstra, 2018). In health care, wearable technology is transforming how strategic businesses approach customization of care for patients through new digital business models and establishing a first-mover advantage in the industry to include using machine learning models for anomaly detection in medical image datasets and classification in the clustering of patients' records (Nayak et al., 2019; Y. Zhou & Varzaneh, 2022). Within time-sensitive service industries like tourism and hospitality, service organizations are BD-reliant, both the internal and external dynamics of a diverse sensitive ecosystem, where real market intelligence, smart data-driven strategies, business intelligence analysis, and integrated functional silos exist to be successful within dynamic business complexities (Najdawi & Patkuri, 2021; Stylos et al., 2021). The data strategy for the industry will depend on how valuable their datasets are to their daily business functions holistically. The siloed approach of disparate organizations holding on to their data will not yield the intended successes of BD management and opportunities to establish a competitive advantage over rival peers. New BD strategies for SMEs is a development priority to determine the positives and negatives of implementing multiple business tasks through better data integration with an organization.

The application of BD has many practical benefits and limitations that must be addressed when implementing data within any SME. Benefits of BD comprise the following: (a) dynamic pricing, (b) predictive analysis, (c) security and fraud detection, (d) supply chain visibility, (e) customization and personalization, (f) customer behavior and interest, (g) customer loyalty, (h) trend forecasting, and (i) innovating business models (Alrumiah & Hadwan, 2021; Sivarajah et al., 2017). A SMEs' BDA orchestration and synchronization of dynamic resource management, permits them to approach maintenance through a different lens of predictive, preventive, and corrective actions, and develop innovative growth strategies for better manufacturing operations (Akpan et al., 2022). Another benefit, the concept of smart circular economy emerged where the finite resources of earth's resources are taken into consideration when leveraging BD to connect information and material data, increasing the operationalization of resource capabilities in decision making for senior executives and senior managers, but also improving sustainability and enhancing supply chain management (Kristoffersen et al., 2021b). For SMEs, some limitations of BD include the following: (a) data growth and analysis challenges, (b) high cost of BD tools, capabilities, and personnel, (c) data privacy, (d) data volume, (e) talent and skills shortage, and (f) data integration (Alrumiah & Hadwan, 2021; Sivarajah et al., 2017). SME leaders are constantly striving to stay ahead of the latest innovation in products and services out in the market that allows for competition, team works, or partnership in improving their return on investments and revenue growth. For this reason, the modern perspective on IT could involve keeping up with the velocity, veracity, volume, and variety of data and information that exists in the natural environment and how best to extract, process, and analyze these vital assets. When organizations understand how the benefits and limitations affect their data as an asset, it may allow for product and service innovations to be the source of functional business units' high performance and profitability.

Big Data

BD is the modern data analytic frontier within the IT environment where the data are necessary for business competitiveness and growth expansion during the digital era of the 21st century. Data can be considered an asset class similar to oil, where companies have large amounts of data at rest, which reflects BD as immeasurable, a data deluge phenomenon, no fixed data threshold, and central to the core business performance of an organization over time through datafication (Alharthi et al., 2017; Carillo, 2017; Kugler

& Plank, 2022; Sheng et al., 2017; Sivarajah et al., 2017). In the 1980s, BD began largely because of the emergence of business intelligence, and later within the new century, the focus was on business analytics and competitive intelligence (Barham, 2017; Luis Casarotto et al., 2021b). BD has been around for decades dating back to early 1960s; because of the limitations of aggregating data, computing power, and low-order data interactions, it was not constituted as a requirement by large corporations (Barham, 2017; Koman et al., 2022; Kopalle & Lehmann, 2021). El-Kassar and Singh (2019) stated that there are three utilization stages of working with large-scale data: (a) BD acceptance – stakeholder engagement with management assurances, (b) BD routinization – organizational governance systems for technology integration, and (c) BD assimilation – the concerned extension of BD technology spread across the organization. Likewise, three levels of BD maturity define how organizations using BD should be classified: (a) aspirational – low BD adoption, but high IT focus on efficiency and automation; (b) experienced – high efficiency and automation, but remains steady-state with few BDA injections; and (c) transformed – high BDA use, high automation, and high efficiency (Barham, 2017). BD evolved to be an integral asset to fast-paced SMEs seeking to leverage data into the new era. There is no shortage of data garnered by one entity when every node can act as a valuable data point for firms to explore and exploit towards high-dynamic competitive advantages.

The amount of data created daily by the world exceeded 2.5 quintillion bytes of data, with 90% being unstructured data, becoming vastly large to handle for SMEs in a digitalized economics (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Sivarajah et al., 2017). Data is considered a new asset class in data science, data analytics, and artificial intelligence, where the scarcity of talent and skills calls into question SME's ability to employ powerful analyzes to predict the future, find trends, and develop insights (Behl, 2022; Madhani, 2022). Manufacturing SMEs have large amounts of data that fit under the definition of BD where the raw data is insurmountable to process manually in a timely manner to make informed critical decisions. Dahiya et al. (2022) acknowledged the importance of the data, information, knowledge, wisdom pyramid which applies observed facts, generated knowledge, and accumulated learning to current business dilemmas. BD differs from the traditional static nature of data in three specific ways: (a) the size and volume of data in scale of publicly available information and commercially available information; (b) historical retrieval of data and data analytics; and (c) BD – unstructured and structured data (Knudsen et al., 2021; Kopalle & Lehmann, 2021; Puneeth Kumar et al., 2018). BD can be characterized with other data types to be haphazard, trans-semiotic, and homogeneous; it is this complex combination of data which makes BD distinctive and generates insights for decision-makers in an organization (Kugler & Plank, 2022). SMEs still seek the strategic key to success in the digital transformation of their firms to survive the changing business environment and achieve sustainable competitive advantage, and BD assists in the innovative process of this transition that can occur for data-driven organizations (Dahiya et al., 2022; El Hilali et al., 2020; Knudsen et al., 2021). With the increase of data, the traditional ways of analytics must transform to consider the rise and frequency of new data created each day, but most importantly, the way to create those business drivers using data is undecided within SMEs (Bartosik-

Purgat & Ratajczak-Mrożek, 2018; Côrte-Real et al., 2019). BD is not typical traditional data analytics but an integration of people, processes, and technologies transformed to value digital outputs that augment human computational knowledge, enhance decision-making, and unlock new organizational capabilities, resulting in the adoption of new business plans and strategic perspectives (El-Kassar & Singh, 2019; Horng et al., 2022). The research scarcity of BD must move past post-adoption stages, aligned more towards competitiveness in the business market regardless of the data adoption stage to give executives and managers confidence in their BD capabilities and analytic information (Côrte-Real et al., 2017; Madhani, 2022). The daily rate of creation, recurrence, and expansion of data in a digital environment known as BD does call for more analytics, faster algorithm developments, and deeper insights into the gathered information.

Data's structured and unstructured evolution will thrive among consumers and businesses daily, delivering critical information to decision-makers who may not have understood what they had in their possession in previous decades. BD is the overarching terminology to describe technologies that capture, store, transform, analyze complex datasets of high volume, variety, veracity, value, and velocity within different formats with three types of BD: (a) machine-generated data – sensors, streaming, video, and satellites: (b) human-generated data – social media content: and (c) business-generated data – transactional, corporate, and government agencies' data (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Koman et al., 2022; Mikalef et al., 2018; Willetts et al., 2020). It is on par with the importance of quantum computing and nanotechnology with the BD scale reaching in 2020 to over 40 Zettabytes or 40 trillion gigabytes, with the number set to expand exponentially by 2022 to $274.3 billion (Akter et al., 2020; Sivarajah et al., 2017). BD does relate to the concept of competitive intelligence. BD is about the competitive nature of varying parties to use data as an asset to glean new information for decision-making purposes to serve strategic managers at all hierarchal levels of business rather than dependence on intuition-based experiences alone (Horng et al., 2022; Luis Casarotto et al., 2021b). SMEs use BD to deliver hidden insights into the data by exploring new market opportunities and exploiting in-depth global knowledge about the external environment, leading to a competitive advantage (Lin et al., 2020). The larger the BD that resides in an organization, the greater the resource capacity needed to explore and exploit the data for executives and senior managers to understand the world around them. BD may continue to be an emerging research field where varying data sources create unique relationship associations that help SMEs leverage insights into key business metrics, leading to decision advantage over competitors.

Big Data Analytics

BD analytics (BDA) is a management research field that deals with data storage and handling through data visualization and integration to provide critical information within knowledge and business intelligence organizations. BDA defines the evolutionary infrastructure, technical tools, and architecture that normalizes large volumes of data into manageable information through the discovery, analysis, and dissemination of data as a service to the end-user (Knudsen et al., 2021; Mikalef et al., 2019; Yanamandra, 2019). BD is a critical strategic innovation for organizations, the parameters for both its performance in efficiency and desired results in effectiveness are tremendously underutilized by most firms (Gupta et al., 2022; Shah, 2022). BDA resides in the ability of firms to use analytic tools to generate insights or outcomes through the investigation of numerous data sources in different domains (Willetts et al., 2020; Zhuang & Ye, 2022). BDA is the next digital edge for productivity, competition, and innovation that provides advantages in product and services improvements, faster innovation periodicities, customer-focused business models, and acceptable data-replication costs (Knudsen et al., 2021; Luis Casarotto et al., 2021b; Shan et al., 2019). BDA is nascent in its analytic approach for SMEs, and the rate of adoption is slow by horizontal and vertical business units where organizations determine their deployment success among the workforce to build analytical models, create distributional reports, explore data visualization, and better integrate data into their business workflows (Sivarajah et al., 2017; Willetts et al., 2020). BDA is the aggregate of multiple layered BD sets that service to enhance SME's innovative process through alignment of both adopting data as a service and to realize data as a service within their organization.

Likewise, data integration is the aim of organizations seeking to integrate their unstructured, semi-structured, and structured data into a cohesive understanding of the dynamic business environment (Alrumiah & Hadwan, 2021). The future of data integration and digital technologies is critical in determining how companies plan to use the information towards driving competitive advantage over competitors in a versatile and open innovative market. SMEs are realizing the power of analytics and human resource to mature their analytic capabilities towards a predictive and prescriptive model over time, and not reactive in nature to internal or external challenges (Arora et al., 2021). The uniqueness of an organization's BD capabilities could allow for data analytics through visualization and integration of data to serve the organization's dynamic requirements, valuable insight extractions, and sensemaking of the information to enable executives and managers in their decision-making process for the company.

The utility of IT may determine growth within a business, which is in keeping with the demands of the consumers through a renewed focus on investment, human capital, and resources to maintain a competitive edge. BDA acts as the lifeblood to an organization's continued relevance in the global business markets, seeking to disrupt their industry with real-time digital data streams, where customer needs (psychological) and competitive forces (structural) exert pressure to meet critical success factors for sustained long-term competitive advantage (Dubey et al., 2019; Raguseo et al., 2021). For this reason, BDA capabilities must ensure that a synchronization and orchestration of both strategic dexterity (talent/resource mobilization) and absorptive capacity (data management/business intelligence) to enable strategic competitive advantage (informed decisions/timely business value) using advanced analytics and computational data models to generate critical decisions that drive insights for executives and managers (Hopf et al., 2022; Mikalef et al., 2018). SMEs depend on BDA capabilities to enhance, augment, and improve managers' decision-making, customer preferences, operational efficiency, BD assimilation, and predictive analytics (Jha et al., 2020). The competitive environment for an organization changed from the industrial revolution to the digital and information revolution, where the strategic scope of an organization aims to adapt to the constant ambiguity within the market at a rate of speed equal to the dynamic nature of the situation

(Ranjan & Foropon, 2021). The accumulation of IT and BDA resources within SMEs can indicate the possible occurrences of IT innovation being established and potential exposure of strategic talent and data orchestration that redefine how BD interacts with the spatial formation of an adaptive competitive advantage over time. What makes an excellent company is an organization that can exceed its dynamic capabilities in response to varying market forces using data to enhance its operational decision-making processes and procedures, leading to control of hyper-turbulent environments and data-agnostic challenges.

Big Data: Five Levels of Analytics Maturity

Data analytics is the summation of information into crucial actionable techniques. Though BDA is constrained by the accessibility of skills, technologies, and tools, data constituted as an evidence-based analysis, allows for the potential towards sensemaking insight extractions from raw data that enhance cognitive processing, intensifies organizational-collective efforts, and surges competitive productivity through different analytic methods (Al-Khatib, 2022; Sivarajah et al., 2017). BDA denotes the analytic application methods that address the consumption and diversity of actionable data based on five different methods (Mikalef et al., 2018). There are five different types of data analytics: (a) predictive analytics, (b) inquisitive analytics, (c) preventive analytics, (d) prescriptive analytics, and (e) descriptive analytics (Cabrera-Sánchez & Villarejo-Ramos, 2020). This section discussed how each of the different analytic methods factors into the decision-making and productivity of a firm’s understanding of the environmental complexities with the business markets.

The first three analytic methods, predictive, inquisitive, and preventive analytics can be examined by executives and managers to enhance their decision-making competencies. Predictive analytics refers to algorithm models that use past reports to forecast future estimates, conduct demand sensing, and provide root-cause based analysis, using machine learning techniques or regression techniques to discover patterns and capture data relationships (Grover et al., 2018; Medeiros & Maçada, 2022; Sivarajah et al., 2017). Etihad Airways conducted predictive maintenance on their extended air fleets to determine appropriate routine upkeep of their assets that go to 89 destinations worldwide with an average of 10 million customers per year (Alharthi et al., 2017). Yanamandra (2019) presented that risk assessment, procurement, and management benefit from predictive analytics to forecast future trends utilizing BD, allowing executives and managers to gauge their next strategic moves towards establishing a competitive advantage over their industry peers. The next analytic method is inquisitive analytics. Inquisitive analytics provides data analysis of why something is occurring, combining both descriptive and historical data analyses about the company's organizational processes (Cabrera-Sánchez & Villarejo-Ramos, 2020). The inquiry format of data analytics allows SMEs to statistically drill down into bits of information that are deemed qualified or excluded depending on the business project (Sivarajah et al., 2017). As part of preventive analytics, executives and managers of SMEs learn what needs to be done, how to do it using data structures, and what options are available to make decisions for the organization (Cabrera-Sánchez & Villarejo-Ramos, 2020). Human input will be crucial to determining the best strategy.

Two of the five analytic methods, prescriptive and descriptive, can help SMEs make sound and transparent decisions about the phenomenon of BD. Prescriptive analytics develops a behavior framework or model that informs the optimal behavior and action through future-optimization alternatives (Grover et al., 2018; Medeiros & Maçada, 2022). Yanamandra (2019) stated that logistics, warehousing, transportation, and manufacturing could benefit from prescriptive analytics, allowing for the narrow focus of raw data sources to solve particular issues using BD. The Dublin City Council adopted the concept of prescriptive analytics when providing innovative city services that allow geospatial data and other real-time data sets to best determine the optimized needs for the consumer (Alharthi et al., 2017). Descriptive analytics provides information on past reports and helps managers understand what may have occurred in the executive of an organization’s strategy (Cabrera-Sánchez & Villarejo-Ramos, 2020; Grover et al., 2018). This analytic utilizes statistical math like frequency, variance, standard deviation, mode, mean, and median to develop visual dashboards for SME executives and managers to digest meaningful business intelligence data to make profound decisions about the company (Sivarajah et al., 2017). BDA ensures that reports can provide current information through raw data to generate timely data that is valuable and advantageous to the organization (Sivarajah et al., 2017; Yanamandra, 2019). These options support SMEs in comprehending which analytic maturity method using raw data to answer business complexity problems while using data to validate their decisions. BDA acquired, stored, processed, optimized, and developed, help to determine how resourceful organizations can become in understanding their intricate value and the information gleaned from data to make holistic forecasts, inquiries, and recommendations about the organization's future directions.

Big Data Analytics Capability

IT is an internal and external tool that connects human capital, financial capital, projects, investments, and other resources through a defined business model, where organizations leverage BD analytics capability (BDAC) to capitalize on productivity and profitability. BDAC refers to the transformative nature of a competitive organization seeking to use BD to uncover new product lines and service assets through three main elements: (a) human knowledge - managerial skills and technical skills, (b) tacit knowledge - culture and organizational learning, and (c) explicit knowledge - data and technology (L. Li et al., 2022; Upadhyay & Kumar, 2020). Medeiros and Maçada (2022) explained that effective BDACs are continuous sequences of operationalized data science techniques through which SMEs acquire insights towards innovative opportunities, contributing to an organization's competitive advantage. For SMEs, the primary organizational foundation is human talent (human skills), financial and capital investment (tangible resources), and data assets (intangible resources) that leverage the BDA's value, BDA infrastructure, and BDAC for strategic optimization, accelerated innovation, enhanced profitability, and accelerated growth of the business (Behl et al., 2022; Grover et al., 2018; Horng et al., 2022; Zhang et al., 2022). Numerous vital concepts align to the creation of new business models and IT to modern theoretical concepts using data to include learning environment, knowledge management, internet of things (IOT), customer intelligence, smart cities, artificial intelligence, data management, and business intelligence (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Luis Casarotto et al., 2021b; Shah, 2022). There will be four analytic concepts highlighted BD intelligence integrated process framework (BDIIPF), digital data stream (DDS), strategic alignment, intellectual and social capital integration and technology integration (SIST), data driven integrated product-process design framework (DD-IPPD), clustering based classifier ensemble method for cost of defect prediction and strategic approach of value identification BD framework (SAVI-BIGD).

Next, I discussed the BDIIPF, DDS, SIST, DD-IPPD, and SAVI-BIGD models. Luis Casarotto et al. (2021b) stated that BDIIPF is a developmental and open system concept where intelligence search, strategic management, BD universe technologies, BD characteristics, and competitive intelligence cycle make up the outline of how an organization constructs a logical path with BD to develop the intelligent needs of the organization, tailored to be an operationalized structure for adaptive BD analysis. Next, Raguseo et al. (2021) explained that the DDS, evolutive business, and competitive intelligence are the object-class representation of digital data streamed through machine encoding and transmission of human behavior that supports digital data strategy, data readiness, and high-quality data conversion at tactical (individual), operational (team), and strategic (organizational) levels of an organization. Barham (2017) defined BD into three stages of analytics adoption by organizations: (a) aspirational, (b) experienced, and (c) transformed. Shi and Wang (2018) proposed another BD analytic concept known as the SIST model, which will evolve strategic management and continuous data management blueprint that allows companies to determine how resource orchestration of internal and external centers demonstrate value over the timeframe of financial investment, human talent, and leadership skills. Uz Zaman et al. (2022) described that the DD-IPPD framework contained a multi-stage decision process for BD design manufacturing where DD-MRS with the right integrated DA PN and DA PPMM supported the technological amalgamation of unexplored opportunities for a firm to succeed in an era of immense datasets focused on design decision space, and data-driven requirements.

Another concept is the CBCEM-CoD model. It is an evidence-based operations management of the core manufacturing challenges using varying BDA techniques for inputs and outputs, numerous BDA insights, and ensemble learning for algorithmic aggregation to support effective decision making and reduce bias in the model for business value (Sariyer et al., 2022). The last analytic concept is the SAVI-BIGD model. SAVI-BIGD is about the value proposition of BD strategic alignment to an SME's business strategic objectives over time-based on five key phases (Lakoju & Serrano, 2017). The five phases can be viewed as a strategic framework for the digital alignment of BD to an organization's requirements, based on the following: (a) strategic vision, (b) implementation road map for BIGD, (c) generation of strategic BIGD goals, (d) determination of data sources, and (e) BD implementation plan (Lakoju & Serrano, 2017). The generation of BD assets can be valued as a potential value to an organization if the organization has several data as a service (DaaS) champions who take the organization's strategic vision and map out cost savings and implementation plans that lead to competitive strategic BD plans. Out of 300 organizations, Lakoju and Serrano

(2017) confirmed that only 45% of successful BD projects reach the completion stage, limiting BDAC opportunities and tools for more strategic operations. Different organizations take each analytic adoption model to justify their operational level of proficiency to determine the maturity state necessary to consider the value, cost, technology, challenges, and benefits that lead to data-centric organizational changes (Barham, 2017). In the subsequent paragraph, the level of analytic adoption is explained for business leaders to better gauge where they are in the spectrum of adopting BD in their organizations.

I elaborated on the background behind each analytic adoption stage, aspirational, experienced, or transformed, centered on defining each data-centric hierarchical level found in any organization. The concept of aspirational analytics adoption resided in analytics with a justified action where leaders determine whether the value of the business using data is worth investing in; Yet, the people, culture, and technology are limited in scope leading to challenges in cost efficiency and revenue growth (Barham, 2017). Experienced analytics adoption defines the guided action through which organizations understand their data and utilize it in their day-to-day operations, but hesitant to fully commit resources to convert to a data-driven centric organization, limited by a lack of technical skills, cost efficiencies, data governance, and revenue generation that affect organizational innovation (Barham, 2017; Li et al., 2022). Lastly, transformed analytics adoption defines the prescribed actions through which managers have accepted data as an essential fabric of the organization’s identity and brand management, leading to business challenges in revenue growth, profitability, and customer retention, while dealing with issues about data accessibility and competing requirements (Barham, 2017). As a strategic value, BDA served as another business model combining three elements: environment factors, IT-enabled dynamic capabilities, and IT resources to achieve competitive advantage (Bartosik-Purgat & Ratajczak-Mrożek, 2018). The varying business models of BD demonstrated that there are different pathways to achieve competitive success with data in any industry, but the key to outperforming competitors still lies in the people, processes, and procedures strategy of an organization. Organizations can establish varying adoption strategies as part of an IT competitive strategy to understand the nexus between their dynamic capabilities and the level of competitive advantage they may face within the changing global market.

BDA is a powerful statistical analytic tool that combines multiple data types, points, and styles in order to solve critical business problems that result in a competitive advantage for the company (Grover et al., 2018). The competitive nature of the digital economy requires a transformation among manufacturing SMEs to embrace BD visualization from disparate sources and formats for actionable insights, adopt the principles of concurrent engineering, and embrace data-driven decision to bring value and optimization for the organizations (Briasouli et al., 2021; Iosif et al., 2021; Madhani, 2022; Medeiros & Maçada, 2022). Organizations determine BD innovation through their contribution to acquiring new capabilities and service generation through the characteristics of volume, variety, velocity, and value using the cloud, high-velocity discovery, and novel data processing algorithms (Luis Casarotto et al., 2021b). Dubey et al. (2019) explained that supply chain management requires BD analytics to help business leaders make better decisions on the strategic direction of their organization. The rapid pace of change involving the digital collaborative environment, does accelerate the nature of digital transformation in a traditional enterprise seeking to understand their adoption status, whether as aspirational, experienced or transformed within the digital marketplace. The modern perspective on IT does involve keeping up with the value, velocity, veracity, volume, variety of data and information that exists in the natural environment and how best to extract, process, and analyze this vital asset. Organizations can thrive and do excel towards high business performance and profitability.

BD Five Characteristics

BD is characterized by five key characteristics, which must be analyzed to understand the generational architecture, technologies, and techniques of BD that define how information is collected, stored, processed, and disseminated as time-sensitive and critical informational packages for decision-makers in any organization, especially manufacturing. With the exponential daily growth of data, there is a paradigm shift among the organization of how to value and represent data within their organization, whereby the end of 2025, it is projected that 463 exabytes of data are created each day (Almeida & Low-Choy, 2021). A recent study defined the 10 dimensions of BD: value, variety, vulnerability, veracity, volume, volatility, visualization, validity, vulnerability, and velocity (Almeida & Low-Choy, 2021; Hassanin & Hamada, 2022). The scope of this research outlined five key elements of BD that reinforced the use of artificial intelligence and large data sets: (a) value, (b) velocity, (c) veracity, (d) volume, and (e) variety. BD characteristics will be expounded below in a detailed description.

Value. Data has a value that SMEs could consider as a growth asset to create new services and products for the organization. The expected value of data is integral to the confidence and trust placed by an organization in decision-making scenarios that lead to a competitive advantage over time for SMEs (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Elia et al., 2020; Li et al., 2022; Uden & Del Vecchio, 2018). There are five dimensions of BD adoption value to highlight along with their definitions: (a) information value – leads to transparency creation of accessible data to support knowledge discovery, (b) infrastructural value – discusses how experimentation enablement leads to improvement of the current infrastructure, (c) transactional value – denotes the customization and personalization of consumers' goods and services which lead to growing revenue streams and gains in productivity, (d) transformational value – extends to new business innovation for the benefit of the organization, and (e) strategic value – combined human-machine support teaming where the IT and business strategies are aligned to be responsive to the business environment (Elia et al., 2020; Li et al., 2022; Symitsi et al., 2021). These are central to understanding and representing BD techniques as a rate of investment and rate of return for the organization. Côrte-Real et al. (2019) determined that less than half (43%) of BDA initiatives by organizations achieve their strategic goal because they lack talent management, mainly in technical skills comprised of data science, machine learning, and statistical analysis.

Velocity. Data velocity refers to the rate of BD change relative to the organization's internal asset and external data requirements to improve its sensemaking of the business environment. Velocity defines the periodicity and rate of data source formulation and accumulation over a specific period, leading to a defined data stream for an organization (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Mikalef et al. (2018) explained that the rate of real-time data versus the rate of superseded data makes a difference in accepting new data that can improve intraday decision-making and increase business agility. Elia et al. (2020) stated that SMEs could use BD to analyze data gathered, exploited, and disseminated to transmit information and exchange information in real-time.

Veracity. Veracity is the scrutiny of the data asset acquired by an SME to determine its reliability in data prediction. Researchers use veracity to explain the credibility, reliability, and integrity of the data acquired and obtained through varying methods (Bartosik-Purgat & Ratajczak-Mrożek, 2018). The veracity of the data can be compromised, as 20-25% of the information on the internet is untrue; BD algorithms and tools control for uncertainty and ambiguity in the data structure (Elia et al., 2020; Grover et al., 2018). Because of the constant threat of cyber-attacks on a network, data security is paramount to safeguard prosperity information and core company secrets to remain competitive in an ever-evolving and changing global market (Grover et al., 2018; Sivarajah et al., 2017).

Volume. Volume refers to the unlimited data sourced from publicly available information to sensors, put together that define an entity’s collection of information (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Mikalef et al., 2018). The term volume is centered on collecting digital information, including unstructured and structured data that are hard to analyze and derive meaningful insights using existing IT tools (Alharthi et al., 2017). Hassanin and Hamada (2022) explained that BD challenges are in the numerous structured and unstructured data facing organizations. More importantly, an increased flow of data created each day becomes unmanageable by one person alone because of the dispositions and dimensions of datasets stored in immeasurable amounts (Côrte-Real et al., 2019; Madhani, 2022). When raw data overwhelms because of data integration or data acquisition and warehousing, the difficulty becomes the ability to trust such data; part of external data collection is based on human-interpreted data (Grover et al., 2018; Sivarajah et al., 2017).

Variety. Variety constitutes the structured and unstructured diversity of data and its accumulative properties (e.g., commercial data, city data, and manufacturing notes) based on varying levels of formats (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Mikalef et al., 2018). Each day, organizations create disparate data sources resulting in a variegation state of data readily available for utilization and application to improve business performance (Madhani, 2022). It is not limited to only known data sources but has expanded to include digital data streams and varying quantitative data sources (Alharthi et al., 2017).

BD Challenges and Benefits

Some SMEs observed BD as a hindrance and barrier to competitive advantage, but other SMEs understood the business value of BD to provide benefit and cost analysis for the organization. BD is an emergent topic for business leaders within a complex business environment because the millions of raw data points based on structured and unstructured data, is a major challenge for SMEs (Bartosik-Purgat & Ratajczak-Mrożek, 2018). The obstacles of BD exist with the following challenges including: (a) lack of data mining ethical principles; (b) alignment of people, processes, and procedures; (c) privacy issues; (d) BD conceptualization; (e) data processing system limitations; and (f) lack of knowledge in data-centric customer analytical approaches (Hossain et al., 2021; Sivarajah et al., 2017). The barrier for BD exists with the following challenges: (a) infrastructure high costs; (b) lack of people and technical tools in data science; (c) lack of organizational cultures centered on data-driven strategic management; (d) shortfalls in multiple data objectives and interpretations; (e) Artificial intelligence and analytics do not gather or create data; (f) human-machine job security debate; (g) regulatory – ethical, legal, and privacy issues; and (h) enterprise cyber and data breaches (Alharthi et al., 2017; Kayabay et al., 2022; Kopalle & Lehmann, 2021; Malthouse et al., 2019; Sivarajah et al., 2017; Willetts et al., 2020).

There are both benefit and cost analyses associated with the use of BD. The benefit analysis of BD includes: (a) reduction of time and cost, (b) increased sales probability, (c) new customers, (d) improved financial performance, and (e) better market information (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Alharthi et al. (2017) examined the three main data characteristics: velocity, volume, and variety among BD versus business intelligence. They found that BD constitutes infinite, real-time, and unstructured data sources, while business intelligence is limited to finite, offline, and structured data sources. The cost analysis of BD includes: (a) data storage, (b) data analytics, tools, and systems, (c) data complexity, adaption, and conversion, and (d) data management access (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Grover et al. (2018)

explained that there are value propositions of BDA: (a) BDA can be valuable, (b) BDA can be rare, (c) BDA can be inimitable, and (d) BDA can be organizationally embedded. Organizations view the critical success factors for considerations center on the following: (a) leadership, (b) functionality, (c) flexibility, (d) time, (e) culture, and (f) cost (Ranjan & Foropon, 2021). Barham (2017) noted that BD is not only imitable and unique as an operational and strategic resource for organizations, but it can enhance, improve, or extend an SME's competitive advantage for a considerable amount of time. The information dominance of an organization does not necessarily lead to a strong performance; it is a mixture of management, technical skills, and processes that achieves the desired benefits and dynamic capabilities for resource allocations. To overcome any limitations, a company's competitive advantage could originate from creating a value-purposed and data-driven strategy based on BD analytics and innovative technologies while ensuring product and service heterogeneity and resource immobility over rivals.

Machine Learning

ML is a subset of AI, where though limited in scope to narrow AI, it is focused on using reinforced learning to help understand the data environment and ecosystem. BD, cloud computing, and the IOT are three fundamental pillars to the strength of ML, in particular exploring and exploiting data at a faster rate of speed using the cloud, enhancing operational efficiencies, and providing information through cyber-physical systems as the catalyst for sensor generation throughout the manufacturing ecosystem (Akpan et al., 2022; Pham et al., 2022; Roy & Roy, 2019; Stroumpoulis & Kopanaki, 2022; T. Wang et al., 2021). Within the manufacturing ecosystem; the hardware infrastructure; data extraction, transformation, and load; and data analysis involve smart manufacturing, where controllers, sensors, and machines move rapid BD processing from device to the cloud, attempting to maximize system-level and device-level performance towards a unique competitive advantage (Saez et al., 2018). To improve manual tasks in manufacturing production lines, ML can assist using computer vision to detect anomalies, automate multi-tasks in classification of parts, identify inefficiencies, and provide critical and timely solutions to resolve problems before they end of the production cycle, leading to an increased fold in competitive advantage for an SME (A. Walker et al., 2021; Younis et al., 2022). Likewise, ML uses minimal human intervention while continually improving its algorithm to provide data-driven insights to senior executives and managers (Jakhar & Kaur, 2020; Lesort et al., 2020; Reis et al., 2020). ML should not be considered a restricted tool only dedicated to financial and health care sectors; it is a cyclical and iterative development that other industries can use to include the manufacturing sector (Chae & Olson, 2022; Patel, 2020). SMEs can construct their ML models to be versatile, predictable, and adaptive to the data environment, though varying variables limit traditional ML techniques to both structured and unstructured datasets (Kitchens et al., 2018). SME executives and managers must be consulted early about their business requirements to apply the proper ML technique and tools to the problem. ML will provide organizations the opportunity to build competitive advantages that lead to market growth, stable R&D innovations, and unique data collection to improve their internal algorithms.

SMEs use ML and multiple data structures to improve the decision-making for executives and managers. There are three defined elements with ML that are part of a data environment: (a) supervised learning – future predictor of events using learning models and BD to improve the trained algorithm, (b) unsupervised learning – unlabeled data used to cluster information for future predictions, and (c) semi-supervised learning – adaptive labeled-data used to correct event predictions (Cabrera-Sánchez & Villarejo-Ramos, 2020; Jakhar & Kaur, 2020). Each of these elements uses the programming language of R/Python to help solve complex and intensive problems involving BD and ML (Farrokhi et al., 2020; Saputra et al., 2022). Likewise, real-time BD streams allow for the execution of timely decision-making and insightful sensemaking for SME executives and managers (Mehmood & Anees, 2020; Rana et al., 2022). Younis et al. (2022) confirmed that ML demand forecasts were more accurate to their defined real-time measurement than traditional forecast models, suggesting accuracy in using ML for value creation while reducing the risk to an organization. Organizations process BD information using clustering, classification or association to improve the accuracy of the models over time through algorithms, ML and statistics, enhancing the data-driven decision for executives and managers and enriching the capabilities of multiple target tracking algorithms through computer vision (F. Li et al., 2021; Rana et al., 2022; Saputra et al., 2022). Long-term ML unification strategies require SMEs to accept experimentation failures as powerful insights and algorithm modifications as a business norm using data professionals, investments, cloud-based metadata registry, and time to build an industry competitive advantage (Patel, 2020; A. Walker et al., 2021). The importance of ML to an SME does highlight that data-driven ecosystems through the integration of BD provide the following benefits along with deep learning applicability in businesses: (a) agile and speed, (b) sustainable and profitable, (c) versatile and scalable, (d) lean and efficient, (e) automated and networked, (f) remotely operated, (g) transparent and ethical, (h) customized and innovative, (i) worker's safety and well-being, (j) reliable forecasting, and (k) automated translation (Priya et al., 2022; Reis et al., 2020; Roy & Roy, 2019). BDA investments can enhance ML business values, where SMEs seek repetitive competitive advantage through reinvigoration of current service and product offerings, new revenue streams, and modernization of their business models.

Strategic Dexterity (SD)

The SD of SMEs can be enriched by offsetting the competitive environment using knowledge resources to set relational embeddedness and learning orientation as the primacy for future digital economies. Strategic dexterity is synonymous with strategic agility, where SMEs must completely understand both the internal and external environment, using knowledge as an asset to drive competitiveness among businesses in the right direction. Kale et al. (2019) defined strategic agility as the organizational fortitude to use in-house assets, external assets, and data to perceive the ambiguous environment and respond quickly to multiple changes, both known and unknown activities, within the firm. Likewise, Medeiros and Maçada (2022) found that data-driven cultures are a set of beliefs and ultimately, data analytic attitudes towards how SMEs embrace the strategic value, responsibility, and management of data utilizations to improve, change, or enhance data-driven decisions through a shared collective set of mannerisms that reinforces cultural norms. Anca-Ioana (2019) discussed how organizations are successful when decision-making, flexibility, and adaptability are executed at the speed of relevancy. For this reason, strategic agility is required in varying marketplaces where firms must surge their resource capacities to keep pace with or exceed rival SMEs, support management control functions through dynamic simulations and real-time analysis, focus boundary spanning behaviors towards partner organizations, and ensure a strong market lead towards widening their competitive advantage (Clauss et al., 2020; Dehbi et al., 2022; Xue et al., 2022). Regardless of the market type, a common trend of strategic organizational dexterity could start with the organization as an entity to bring managers, employees, and other external stakeholders towards achieving similar data-driven goals. It is not about crisis planning operations, but it is centered on strategic dexterity, where reacting meticulously and diligently to market changes of foreseeable and unforeseeable events proactively through BDAC with holistic resource plans allows SMEs to achieve success through strategic data behavioral changes and analytic importance to solve SME business problems.

SD is an important concept of strategic management to include its metamorphoses into developed and shared networks of data-driven SMEs. SME managers and executives are provided the flexibility to configure the organization's resources, impact and execute enterprise innovation, and develop enterprise networks that adapt to ambiguous market conditions and uncertain global environments (Lin et al., 2020). SD is about firm leaders' flexibility in responding to volatile and complex market environments that exploit existing resources and capabilities through a cohesive and shared network to explore new opportunities through a desired, visionary, and committed learning system (Ahammad et al., 2021). The nature of SMEs' digital network supports the efforts for competitive advancement in manufacturing that transcend the typical call for differentiation, cost, and institutional advantages within a given market; the enhancement and adaptability of a digital strategy allows an SME to compete on a global scale (Ighravwe & Oke, 2018; Sun & Wang, 2022). In this subsection, the expansion on relational embeddedness and learning orientation will be related to the strategic dexterity of an organization in an uncertain business environment.

Relational Embeddedness

The rapid evolution of data and the pace of technology are not surprising in a networked business environment. Disruptive technologies involve data-driven efficiencies in the system that support access to new information, provide real-time understanding, and transform data as part of its core values through BDA and the IOT (Aryal et al., 2018). Organizations have begun to seek other methods to gain competitive advantage, firm agility, and responsiveness in the global business market to determine how best to tailor their strategies. Relational embeddedness is about the strong ties, trust, and shared system found in a competitive and data-driven organization seeking long-term success to transform their internal and external perspective of the global market environment (Dhanaraj et al., 2004). Strong ties refer to an organization that builds strong, cohesive ties rooted in a firm's networks through exploiting and exploring knowledge (Sheng et al., 2017; Wu et al., 2020). Trust is about the social relationship built over time among managers and employees, and stakeholders and external networks that share information exchange to reduce impediments towards a firm's success (Wu et al., 2020). Shared trust is about allowing organizations deployment of resources and capital to improve societal challenges in return for securing long-term competitiveness through product reexamination, value chain enhancements, and collaborative partnerships (Omar & Madzimure, 2022). A notable area involves SMEs that seek organizational stability in the long-term through talent analysis planning of key skillsets and talents to help shape future growth of the organization (Saputra et al., 2022). There is no doubt where demand for manufacturing human resource talents and skillsets in data science, AI, and algorithmic techniques will come, only leading to growth in SMEs.

A firm creates success when network cohesion and organizational conviction are realized and aligned with the internal and external resources of the organization centered on a standard set of values among its networks that reduces mistrust and enhances the company's mission and enterprise knowledge (Wu et al., 2020). Knudsen et al. (2021) summarized that the digital environment strengthened self-reinforcing network effects that amplified the creation of data-driven and automated demand-side economies of scale regardless of physical location. Sheng et al. (2017) explained that SMEs could integrate business management and digital transformation through the fusion of disparate data sources to be flexible in their responses to reshaping the strategic actions of executives and managers. For this reason, a firm's relational network, shared mission, value, and purpose can help senior executives and managers use all available data, creating cultural norms and mutual recognition to drive business growth and make informed decisions for the organization's benefit. Through the normalization of an organization's social capital, cohesive mutual networks, and shared understanding, internal and external stakeholders will buy into creating a digital management strategy that seeks to use the hybrid interactions of knowledge and information to create new insights and drive future market opportunities.

Learning Orientation

The future of data integration is defined by how a firm creates a competitive advantage through a learned system that molds and conceptualizes into a versatile and open innovative structure. Russell and Smorodinskaya (2018) stated that organizational leaders that forecast plans are doomed to fail and need to focus on nonlinear innovation to create new knowledge and diversify the innovation ecosystem. Out of the four typologies of firms using digital technologies based on BD and network effects, Knudsen et al. (2021) described that the most stable competitive advantage typology is data-driven network firms, and their exploitation and exploration of active learning systems. A systematic integration of IT assets helps in packaging data streams (real-time access), developing information (data authenticity), and creating knowledge (versatility of applicability of the captured data) towards active, actionable, and data-driven insights that support the digital transformation of SMEs (Dahiya et al., 2022; Shah, 2022). The innovation system of learning requires good data quality and management practices to increase an SME’s internal and external processes, while shoring up its firm’s knowledge, performance, and capabilities. An SME builds knowledge creation systems that enhance its dimensionality of value, velocity, veracity, volume, and variety to support higher readiness in implementing and executing data-driven competencies towards a sustainable competitive advantage for the organization.

Learning is part of an evolutionary cycle regardless of the organizational strategy. Lesort et al. (2020) detailed that continual learning within data-driven organizations involves disparate and small datasets through specified algorithmic developments focused on prior knowledge, data availability, memory, and AI supervisions centered on ML. For this reason, Thomas (2019) stated that technology convergence is the fusion of complementary technologies that enable the creation of new activities towards a pathway of competitive advantage, where digital technology acts as an enabler of different business units' synergies and integration of information to help decisions, plans, and strategies interconnect for a smooth execution flow. SMEs can permit active data ecosystems using an application programming interface that provides real-time data sources to create complementary BD innovation systems (Huang et al., 2020). Data convergence is vital for organization to better understand their strategic assets. This will be critical as SMEs move data sources from descriptive in nature to predictive to comprehend the complexities of the business manufacturing landscape.

In a complex business environment, relationships, trust, and communication will assist senior executives and managers in navigating the uncertainty terrains their organization may stumble across conducting business activities locally or regionally. An organization can pivot through uncertainty by determining its learning orientation through three ordinal subscales; commitment to learning, shared vision, and open-mindedness (Baker & Sinkula, 1999). Wu et al. (2020) described that firms' local and global perspectives on competitive advantage require diversification, learning systems, and internationalization to adapt and adjust resources through continuous organizational learning. An organization will begin to learn and share its vision by acquiring knowledge internally. Arora et al. (2021) stated that internal interactive training and new e-learning methods in data analytics, ML, or AI can help organizations build up cost-effective, rewarding, and efficient results that contribute to an organization's success in performance appraisal and employee retention. As an SME reaches capacity through data mining, it must expand to absorb and tolerate external data sources of quality and substance that provide insights into the current business problem through learning analytics (Matsebula & Mnkandla, 2017; Shah, 2022). A firm's business culture, shared network, and trust does ensure an organization does not operate in a vacuum but thrives with relational nodes of shared purpose among internal and external stakeholders into a better state of business affairs. This study may be beneficial because it could contribute to a better understanding of strategic dexterity, which looks at the flexibility of management to shift resources, skills, talents, labor, and costs to meet ongoing challenges within a dynamic global environment.

Absorptive Capacity (AC)

The power of data analytics does remain in retrieving data-rich information, which a company can collect from an individual or an entity to expand data to wisdom within the complex business environment. AC defines the level of resource capacity that SMEs can absorb (identify, assimilate, and transform) as knowledge through the equilibrium discontinuities of uncertainty for both exploratory and exploitative BD ecosystems (Grover et al., 2018; Shah, 2022; Y. Yan & Guan, 2018). AC is about the iterative process of conducting exploration and exploitation of external knowledge to determine varying learning techniques that create new assets resulting from the previous information through exploratory, transformative, and exploitative discoveries (M. Y.-P. Peng & Lin, 2021). When the market will saturate with multiple opportunities for goods and services to be exchanged, customers are in control, leading organizations to compete faster to keep up with market expectations, demands, and reactions in a timely fashion. SMEs need to develop knowledge management and business intelligence strategy based on BD that allows for accelerants in innovation to compete with uncertainties in the global market (Quaye & Mensah, 2019). Within AC, data are a crucial element for the survival of digital businesses in the future. Data must be inclusive of its environment.

BD is a common theme in today’s IT environment, where data has become the new strategic asset to a business' competitive nature and expansion. Organizations are responsible for ensuring the abundant data is not saturated in its collection, resulting in stale and insufficient outcomes. AC ordinal subscales are diffused into two higher-order constructs, potential absorptive capacity and realized absorptive capacity, which has the following sub-variables of acquisition, assimilation, transformation, and application (Camisón & Forés, 2010; Cohen & Levinthal, 1990). Wu et al. (2020) explained that AC is about how an organization conducts resource intake management of data to create value. This is done through three approaches: (a) resource integration, (b) resource reconfiguration, and (c) acquisition and merger. This is aligned to the three subvariables above: (a) acquisition and assimilation – defines the acquisition and merger approach of data management; (b) transformation – refers to the resource integration of data; and (c) lastly, application – denotes the resource reconfiguration that is required to ensure data success for the organization (Harris & Yan, 2019). Wu et al. described IT assimilation as data storage with no value, meaning it has no dynamic capability, while IT business value is taking data as an asset with an IT tool to understand how best to leverage information through the following: (a) electronic data interchange, (b) knowledge management systems, and (c) enterprise resource planning. Wu et al. presented their main research findings centered on relational embeddedness positively affecting PAC and RAC, while AC allows an organization to conduct knowledge activities and create new perspectives. The importance of AC lies in the organization’s dependability, internal and external data, and its cross-functional and operational data to advance knowledge into wisdom. By absorbing information into the organization, there will be an opportunity for an organization to either take the direction of IT assimilation or IT business value.

Competitive Advantage (CA)

CA is the spatial and time dimensions of Porter’s theory of CA, where nonlinearity gives an advantage to those SMEs based on network effects, integrated strategies, and knowledge absorption to compete in an open digital market and era of digital transformation. Porter introduced the term CA as the aggregation of an SME's self-reinforcing and networked ecosystem of dynamic resources that are hard to imitate or replicate by rival organizations (Porter, 2001). CA defines the internal and external dynamic capabilities of a firm that will not erode over time, maintain a tenable position, and overcome limitations in creating value over rivals through three absorbed and integrated strategies: (a) differentiation, (b) cost, and (c) institutional (Knudsen et al., 2021; Madhani, 2022; Mikalef et al., 2018; Shan et al., 2019). In manufacturing, SME leaders develop their competitive advantages through internal core competencies, unique specializations, ACs, and customizations strategies to vary from their business and industry rivals through knowledge absorption, creating new and different product offerings and service advances (Gonyora et al., 2022; Ighravwe & Oke, 2018). The age of digital transformation coupled with BD and the IOT will ensure manufacturing SMEs gain knowledgeable insights, expansive datasets, and skilled employees to take the organization to the next strategic level.

Manufacturing SME leaders constantly pursued emerging technologies to develop novel outcomes that improve productivity while gaining a CA. CA is about the finite resources, unique human talent, and networked strategy that establishes hard to imitate organizational products and services provides cost advantage for competent organizational outcomes and finds new opportunities to overcome complex and unambiguous business challenges to outperform rival competitors (Barham, 2017; Kristoffersen et al., 2021b; Liu et al., 2018). The pursuit of a data-centric approach allows disparate business functions to address complex issues and challenges in a timely manner through BDAC, discovering new insights, finding new materials, and establishing stronger internal and external processes, which lead to a better operational and strategic understanding of the business environment, leading to competitive advantage (Al-Khatib, 2022; Dong et al., 2022). A firm’s positionings revolve around differentiation, cost, and institutional advantages found in the theory of CA, which are based on the business environment, resource access, and time management available to SMEs (Bartosik-Purgat & Ratajczak-Mrożek, 2018). In the subsequent paragraphs, the CA ordinal subscales are highlighted: (a) differentiation advantage, (b) cost advantage, and (c) institutional advantage.

Differentiation Advantage

SMEs will seek to differentiate themselves over rivals in products and services to consumers and business through BDAC capabilities, IT convergence and digital fusion, and cloud computing using BD as a strategic asset. SMEs develop differentiation strategies through a comparison of other competitors' offerings by expanding their loyalty reward programs, achieving inimitable product status, skilling employees to support quality services and learn new innovative techniques, lowering service-cost pricings, exploring data-driven optimization models for low-cost solutions, branding the organization effectively, and meeting the consumer expectations on a timely and consistent basis (Pu & Yan, 2021; Wanjogo & Muathe, 2022). With the evolving business environment, organizations could strive to use new emerging technologies, procedures, and techniques to differentiate themselves from competitors (Thomas, 2019). BD has led SMEs to adopt BDAC capabilities to differentiate services and provide distinctive product value from entrants using BD (Kaleka & Morgan, 2017; Razaghi & Shokouhyar, 2021). Thomas (2019) suggested that IT convergence and digital fusion strategies based on Chesbrough's open innovation concept allow organizations to conduct BDA to enrich their optimization for customers and clients rather than dwindling limited SME resources. As the globe moves to hyper-competition, data processing using the cloud will be necessary to enhance customer satisfaction, accelerate innovation, and compel global consumers to be part of an experience (Power & Weinman, 2018). SME leaders will develop their BD strategy as differentiation from others because the focus of internal boundaries only limits the capability of SMEs seeking to succeed in the long term.

Cost Advantage

There are two foundational types of cost-efficiency strategies, bargain pricing to reduce cost and differentiation strategy to charge more for premium, that link cost leadership to CA which are essential to maintain dynamic cost pricing for consumers and command market share (Madhani, 2022). T. Wang and Gao (2022) explained that there are several cost management methods in enterprise manufacturing that SME leaders must consider in their strategy development to include actual cost, standard cost, and testing cost. Each cost strategy is vital to better understand how best to manage cost, utilize data effectively, promote BDA decision-making, narrow the solution space of complex problems, and obtain satisfactory results within an advanced intelligence manufacturing (T. Wang & Gao, 2022). Export-oriented SME manufacturing leaders can adopt a wider range of cost advantages and leadership in delivery dependability, cost-reduction strategies, competitive pricing, customized production, and quality because of their agility, responding nimbly to consumer demands and getting faster outcomes within product development (Jahed et al., 2022; Wanjogo & Muathe, 2022). The confirmation of cost leadership for an SME is ineffective alone and must be combined with differentiation advantage to be a force multiplier to be considered a competitive advantage (Ighravwe & Oke, 2018). Varying international sourcing strategies are essential for SME leaders to diversify their sourcing strategies using BDA to achieve high-quality product manufacturing and low costs to consumers (Kaleka & Morgan, 2017; Razaghi & Shokouhyar, 2021). SME leaders could view pricing innovation as a reaction to customer demand in the digital environment and enhance ways to provide alternative cost mechanisms to deliver strategic competition for the organization (Jahed et al., 2022; Quaye & Mensah, 2019).

Institutional Advantage

Organization leaders can enhance their BD competitiveness when executives and senior managers acknowledge the institutional advantage of their human talent, capital resource, and authoritative permission as part of their dynamic capabilities to generate value for long-term strategy growth. An organization can lack strategic focus towards digital innovation when they do not have employees with knowledge, skills, expertise, and specialization in BDA for competitive advantage (Willetts et al., 2020). Executives and senior managers could develop a capital resource plan that transitions the institution from a stovepipe framework to a digital data fabric that weaves the BD assets of the organization seamlessly together. Behl (2022) explained that organizational culture is essential for any SME’s business survival focused on team agility, dynamic competitiveness, and IT adoption as institutional advantages. For this reason, companies must learn to have a cooperative style of engaging their business, environmental, and regulatory pillars, which leads companies to be valued and trusted members of societal change leading to an authoritive permission to push the boundaries of science and technology towards actionable insights and competitive advantage (Bartosik-Purgat & Ratajczak-Mrożek, 2018; Willetts et al., 2020). By placing people, processes, and procedures first, executives and managers can leverage the organization's dynamic capabilities to gain momentum using their BD strategy to gain a competitive edge over time. Disruption can be a nonlinear vector and approach in data management which may require organizations to break through the hype to realize their full potential in the marketplace, and expanding the opportunities with clients and consumers to gain a relational outlook of the domestic market.

Organizations can seek to maintain an SME competitive and diversification strategy against business failure prospects through strategic alignment of AI and ML as central to corporate success. The utilization of cloud, BD, digital empowerment, and AI are vital components to an SME's strength where the organization leaders propagate their strategic acceleration of enterprise data to gain value and competitive advantage in the digital business environment (Sun & Wang, 2022). An organization's AI/ML system development based on the integration of real-time data, ML, and automation allows SMEs to be competitive where emerging patterns reveal quickly, allowing institutions to build a comprehensive plan prior to execution with authoritative consent (Farrokhi et al., 2020). An organization's leaders must understand the market by sensing, seizing, and reconfiguring dynamic resources capabilities to achieve a first-mover advantage, necessary to have a competitive edge over rivals (Akter et al., 2020; Cao et al., 2022). An organization's agility is about its dexterity and flexibility in varying business functions of AI and ML necessary to keep pace with changes in the IT environment. By acknowledging the institutional advantage, company leaders can develop unique capabilities central to their operations that allow for continuity of business with little to no downtime while enhancing the BD operational functions of the company, protecting people, equipment, and intellectual property, and dealing with finite resources constraints effectively.

Transition

In Section 1 I demonstrated the critical argument regarding AI, ML, and BD to transform manufacturing SMEs into competitive leaders within the future digital economy. Some SME manufacturing senior executives and managers in the United States do not know whether a relationship exists between SD, AC, and CA. I used a quantitative correlational study to examine if a relationship exists between SD, AC, and CA. I described Teece et al.'s DCV theory that examines the interdependencies of firm resources, the internal and external knowledge of the environment, and the augmented path dependencies, to handle rapid technological changes.

Section 2 will include the justifications about the role of the researcher, list participant criteria, and describe the research method and design along with the population and sampling. I will address the components of ethical research, data collection instruments and technique, data analysis, and the data's reliability and validity. Section 3 will comprise of the findings' presentation, applications to professional practices, implications of social change, recommendations for action, recommendations for research, reflections, and conclusion of the study.

Section 2: The Project

This section starts with a reiteration of the purpose of the quantitative study. In this section, I discuss the researcher’s role, research method and design, population and sampling, and data analysis strategy. A detailed description of the research ethics and the data collection instruments, techniques, and analysis are also provided. This section concludes with an explanation of the validity and reliability of the study.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA. The independent variables were SD and AC, while the dependent variable was CA. The target population for the study were SME manufacturing senior executives and managers in the United States. The implications for positive social change include enhancing employee productivity in data usage and advocating for sustainability efforts within underserved and underrepresented communities towards a digital economy.

Role of the Researcher

In quantitative research, the role of the researcher consists of (a) measuring the operationally defined constructs, (b) describing the level of measurement and statistical analysis of the variables, and (c) presenting an objective interpretation of the study results (Abulela & Harwell, 2020; Zyphur & Pierides, 2020). I used Statistical Package for the Social Sciences (SPSS) software to manage and analyze the data (see Bala, 2016). I had SME participants from the United States fill out and complete an online survey through SurveyMonkey (see Appendix B). I used multiple social media sites, such as Twitter and

LinkedIn, to send out the invitation to participants. I do not have any affiliations, principal holdings, or shares with any manufacturing industry sectors or did I know the SME executives and managers who participated in the research study. The data collected will be stored securely for 5 years while adhering to strict ethical principles.

The role of a quantitative researcher centers on research integrity and ethics, which requires them to be unbiased, valid, and truthful to potential participants in the study (Braun et al., 2020; Edwards, 2020). Ethics are a set of guiding principles that morally and virtuously expresses the morals, characters, and values of a researcher (Scipanov & Nistor, 2020). Because there are inadvertent consequences that can occur in a research study leading to distrust (P. Ellis, 2019a), it is important to follow guidelines, like *The Belmont Report,* which centers on respect for persons, magnanimity, and justice (Brien, 2008; National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979; Saunders et al., 2015; U.S. Department of Health & Human Services, 2020). There are also professional standards to adhere to when dealing with a population or sample size, where ethical behavior is paramount (Samuel & Derrick, 2020). A researcher must consider the treatment of a targeted population through providing unbiased information, limiting language barriers, and ensuring voluntary survey participation (P. Ellis, 2019b; National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979). I completed my Collaborative Institutional Training Initiative program on *The Belmont Report* and received a certification for my completion of the ethics course with the ID# 36545289 (see Appendix A). During the study, I respected the autonomy of participants by not placing any pressure on them to participate, and all participants were explained their rights as participants found within *The Belmont Report*. I was honest and respectful with my participants, provided an unbiased letter of invitation and asked volunteers to participate in the study based on anonymity without reprisal or undue influence of their responses.

Participants

Study participation is important to research and requires participants' consent to minimize harm (P. Ellis, 2019a; Peled-Raz et al., 2021; Wendler, 2020; Xu et al., 2020). The participants' eligibility criteria help advance the generalizability of the research study (Weng et al., 2010). The participants in this study included SME manufacturing senior executives and managers in the United States who dealt with the North American Industry Classification System (NAICS) 334, labeled computer and electronic product manufacturing. NAICS is a job standardization occupation system used in the U.S. economy, with its last update in 2017 (North American Industry Classification System, 2017; U.S. Census Bureau, 2020a). NAICS 334 has 30 different submanufacturing industries associated with communications, computers, electronics, and semiconductors (NAICS, 2017; U.S. Census Bureau, 2020b). Participants had to meet the subsequent inclusion criteria: (a) be a SME executive and/or manager in the United States; (b) use BD, ML, or AI daily in business processes and workflows; (c) have management or IS experience within their business; and (d) be classified as part of NAICS 334.

As a doctoral student, it was important to present ethical questionnaires as to not to bias the outcomes of the study. With this doctoral research study, I aimed to provide business strategies to SME chief executive officers (CEOs) who seek to effectively train their employees in AI. The procedures for access to these participants requires informed consent, ensuring the study's reliability and validity (Snell, 2018). Research must protect the privacy of individually identifiable health information and human subjects involved (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979). Since I conducted a quantitative study, the questionnaire was stored on SurveyMonkey to collect data anonymously. The survey was distributed to unspecified personnel using social media with a 6-month deadline ending November 27, 2022.

The strategies employed for establishing a working relationship with participants during the current, global, COVID-19 pandemic adhered to the Centers for Disease Control and Prevention guidelines. First, I developed a data use agreement and letter that informed all participants about the intent of the research and their voluntary participation with no monetary incentives. I also included publication restrictions stating that no company's information or affiliates would appear in this study. All feasible precautions were followed and the study data will be stored within a safe for the next 5 years to include any employee data. The study has merits with proper adherence to the rights of participants and local laws being followed based on Centers for Disease Control and Prevention policies and regulations.

Research Method and Design

Depending on a researcher's worldview, research can be conducted using one of three methods: quantitative, qualitative, and mixed (Folajogun, 2020). A researcher chooses a method based on how best to frame the questions toward possible solutions

(Monroe et al., 2019; Rechberg, 2018; Rumens & Kelemen, 2012). I chose a quantitative correlational design because it allowed for the collection and analysis of numeric data to create new insights into previously held theories, explaining the phenomena observed in this research study.

Research Method

In this study, I employed the quantitative research method. Edwards (2020) stated that quantitative research is about the pragmatic inquiry of observations evaluated through various statistical analyses and packages to draw extrapolations between the relationships of theoretical constructs based on concrete empirical parameters. Researchers are allowed to infer on these constructs' definitions and meanings that can hold a numeric value for future comparative analysis. A quantitative researcher uses deductive reasoning based on probabilistic and empirical evidence to understand the specific phenomena and ensure the generalizability, replicability, validity, and reliability of the research study (Kankam, 2020). Because of the particularistic nature and objective approach of quantitative research, the magnitude of the data allows researchers to determine the cause-and-effect nature of the analyses between multiple independent and dependent variables to determine the research's final statistical outcome with a degree of certainty (Ahmad et al., 2019). I tested whether there is a statistical relationship between SD, AC, and CA by using the quantitative method.

Conversely, qualitative research methodology involves narrative summaries, personal experiences, and interviews among people, entities, and groups to understand the phenomena in its natural setting (Cecez-Kecmanovic et al., 2020). Qualitative research is the best approach to answer a research question in two ways: (a) capture participants' positions through their words to help explain a phenomenon and (b) provide a deeper subjective understanding of participants' observations and experiences on a topic (Denny & Weckesser, 2019; Pieridou & Kambouri-Danos, 2020). Qualitative research relies on words and narratives to tell a story (Morgan, 2018). Use of qualitative research allows interviewees to provide exhaustive rigor by expressing their thoughts in response to open-ended questions (Ahmad et al., 2019; Roberts et al., 2019). The current study's objectives were not based on a storyline or historical account about SD, AC, and CA; therefore, the qualitative method was not appropriate for this study.

Mixed-method research involves integrating quantitative and qualitative methodologies as a hybrid format and used by a researcher to balance the outcome that emerges to answer a research problem through careful consideration of the evidence (Kluge et al., 2019; Morgan, 2018; Sahin & Öztürk, 2019). Mixed-method approaches can be time-consuming, complex, and challenging when dealing with multiple quantitative and qualitative data sets to address research questions (McKenna et al., 2020). Using a mixed-method approach would have limited me in my objective approach and timely delivery of the study, which would require both in-depth investigations and interviews to include the statistical surveys of the relationship between SD, AC, and CA, so this method was not appropriate for this study.

Research Design

I selected the correlational research design for this study to account for the strengths and weaknesses among two or more variables because I was seeking to understand the statistical test related to each association's strength, significance, direction, and degree (see Seeram, 2019). A critical aspect of this design rests on not determining cause and effect based on situational phenomena (Bloomfield & Fisher, 2019). The variables' characteristics, multiple relationships, and predictions are part of the correlational design (Martin & Bridgmon, 2012; Watson, 2015), and I used this design to examine the relationships among SD, AC, and CA.

I also considered the quasi-experimental and causal-comparative research designs for this study. When there is a lack of strict conditional controls found in the experimental research design, a researcher uses two comparative groups to examine the quasi-experimental relationship, which determines the effects that one variable has on the other variable (Abramson et al., 2018; Bloomfield & Fisher, 2019; Kluge et al., 2019). There was no controlling variable associated with the current study, but this would have limited the measurement and operationalization of the dichotomous variables toward a possible outcome (see Field, 2013; Head & Harsin, 2018). A researcher uses causal-comparative research to investigate the pretest and posttest design of the variables to determine the utility of the dichotomous measure of two groups (Blakeslee, 2020; J. Lee, 2008). The quasi-experimental and causal-comparative designs were inappropriate for the current study because they both lack the statistical significance of relationships and random data sampling among variables.

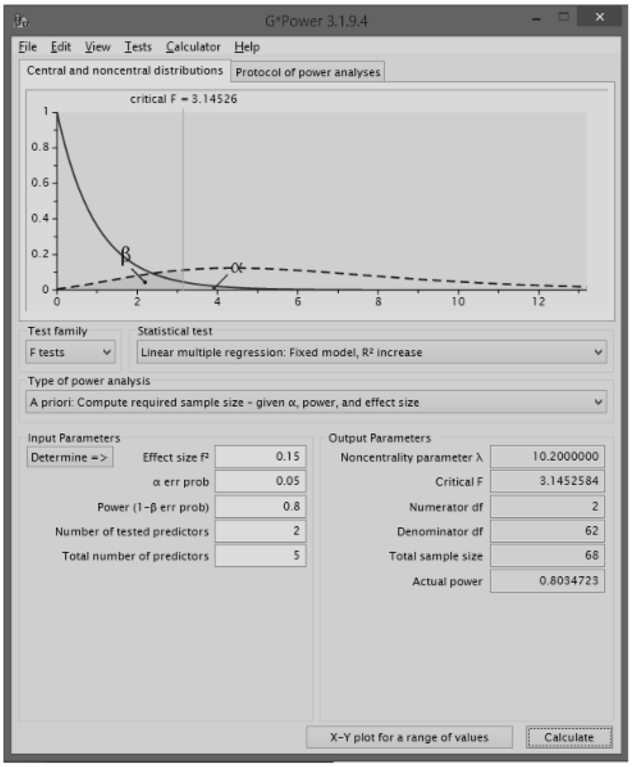
Population and Sampling

The target population for the study was SME manufacturing senior executives and managers in the United States. The SME workforce distribution ranges in the following number of employees and size class: (a) under 10 (Size Class 1 to 2); (b) 10–24 (Size Class 3 to 4); (c) 25–99 (Size Class 4 to 5); (d) 100–499 (Size Class 6 to 7); (e) 500–999 (Size Class 8); and (f) 1,000 or more (Size Class 9; (Gartner, 2021; Headd, 2000; U.S. Bureau of Labor Statistics, 2021). The NAICS, size standards, and table of small business standards determines the classification of a company's employee size and size class (U.S. Small Business Administration, 2021). The Small Business Administration's (2021) classification of NAICS 334 is a label for an organization with more than 1,000 employees and size class of 9 (U.S. Department of State, 2019).

I conducted a power analysis to determine the minimum sample size needed for this study using the G*Power tool, which is software used to compare varying correlational constructs (see Faul et al., 2009). The sample size is a portion or a part of a population represented within a collected data. The holistic concept requires the sample design and sample size to be acceptable to determine the population's confidence and precision (Bougie & Sekaran, 2020). The purpose of a power analysis is to estimate the sample size for a given population through practical and prospective statistical tests (C.-Y. Peng et al., 2012). The relationship between sample size and statistical power lies in the effects of increasing either element's sizes; the statistical power refers to the probability of the rejection of the null hypothesis when it is untrue (Boukrina et al., 2020). I used G*Power Version 3.1.9.4 to calculate the sample size, setting the F test power ($1-\beta$) at .80 for the two independent variables and one dependent variable to verify a medium effect size of f2 = .15 at a 5% level of significance in order to quantify the distance between variables, resulting in a minimum sample size of 68 (see Figure 1).

Figure 1

*Graphical Model of G*Power Analysis*



Ethical Research

The care of the participant should be a priority of researchers. *The Belmont Report* recognizes the importance of research ethics, human dignity, risk-benefit assessment, and research boundaries (Beauchamp, 2020). Conclusions, believability, and reliability center on moral and ethical considerations that establish credibility (Firestone, 1987). Researchers must follow ethical guidelines for the responsible treatment of human subjects to ensure research ethics and integrity. I conducted this study after receiving the approval to do so from the Walden Institutional Review Board (IRB; IRB Approval Number: 04-29-22-1022915).

I provided participants with an informed consent form as part of their survey. Samuel and Derrick (2020) stated that the informed consent form provides participants with an explanation of the study's purpose, confidentiality, data collection, and data usage. All participants were over the age of 18 years old. Saunders et al. (2015) stated that participants must voluntarily take the survey and have the option to withdraw from the survey if requested. Researchers have obligations to ensure the safety and security of their participants from any harm when using digital technology for surveys (Curran et al., 2019; Kraft et al., 2019). I used SurveyMonkey to anonymously collect data. Having the participants complete data use agreements was also a part of taking the survey.

Establishing good data security measures also requires researchers to think of ethical compliance procedures, data retention protocols, and the storage of sensitive data (Briney et al., 2020; Cockcroft & Russell, 2018). I will store participants' information and all data collected on a secure, removable, password-protected USB drive along with all physical notes and documents in a personal safe in my home office for the next 5 years. As a storage backup, I will have a digital, password-protected cloud storage file using Apple cloud storage to secure the data and information from unauthorized access. I also satisfied cautionary data requirements by using an independent data survey tool to collect personal data online. After 5 years, I will permanently delete all electronic files and shred all notes and printed documents.

Instrumentation

Quantitative instrumentation refers to the appraisal of the concrete data analysis alongside varying variable domains to decide how the psychometric properties result in the validity and reliability of the data (MacGregor, 2020). I will use the instrumentation developed by Wu et al. (2020) concerning SMEs' strategic agility, BD, and CA (See Appendix B). Wu et al.'s survey contains four sets of construct variable domains and 13 ordinal subscale domains including SD (relational embeddedness and learning orientation), AC, and CA (See Appendix D). The 13 ordinal subscale domains refer to their associated high-level construct in relational embeddedness, learning orientation, AC, and CA. Relational embeddedness ordinal subscales are strong ties, trust, and shared system (Dhanaraj et al., 2004). Learning orientation ordinal subscales are the following sets, commitment to learning, shared vision, and open-mindedness (Baker & Sinkula, 1999). Absorptive capacity ordinal subscales are diffused into two higher-order constructs, potential AC and realized AC, which has the following subvariables of acquisition, assimilation, transformation, and application (Camisón & Forés, 2010; Cohen & Levinthal, 1990). CA ordinal subscales are differentiation advantage, cost advantage, and institutional advantage (K, Z. Zhou & Li, 2010).

Based on a confirmatory factor analysis, Cronbach's alpha coefficients for the instrument are .770 and .0896, which indicate high reliability, great convergent validity, and good discriminant validity (Wu et al., 2020). Cronbach's alpha measures the internal consistency of the population estimate through a continuous construct scale, normal distribution, adherence to tau equivalence that tests the index of the composite reliability higher than .70 (McNeish, 2018), with a minimum variance of above .50 (Olvera Astivia et al., 2020). To increase confirmatory factor analysis reliability and validity, quantitative researchers developed the use of Cronbach's alpha score as the best instrument to measure similar characteristics found in constructs of a survey that are fit for purpose (Benek & Akcay, 2019; Taber, 2018). Cronbach's alpha determines the internal consistency levels within interrelationship questions (Emerson, 2019). Though a high Cronbach's alpha value may occur between 0 to 1, it only indicates a high correlation between the participant's survey responses and does not need more than one data collection to determine reliability and validity (Emerson, 2019; Schrepp, 2020). The Cronbach alpha scores of Wu et al.'s (2020) study enhanced the need to use the survey in other global locations.

Each independent variable composite scoring reinforced SD, which consists of relational embeddedness (RE) and learning orientation (LO).AC is the second independent variable providing a reliable instrumentation process. My research will include the exact composite scoring domain connected to the dependent variable (CA) measurable within this study. Two changes need to occur to ensure the instrument reflects the locality of the population and intentions of this research involving BD, which consists of first changing the word *foreign* to *domestic*. Though the study focused on international SMEs, it lacked the understanding of how the complexities of the business environment could affect the domestic SMEs competing within global, volatile, and uncertain global markets. For this reason, the study will focus on a domestic audience, and RE and LO combine into a single term known as SD. SD, as a construct, is abstract and subjective. RE and LO measures will not cause issues and are inferred as SD to understand their relationship better. Both variables define how senior managers view the combination of labor, knowledge, and organization as part of a working strategy for success. Wu et al.

(2020) required no publisher permission to use the survey instrument, only that their work is cited appropriately in any future study (See Appendix C). Since this is an open-access research article, no license statement or publisher's consent is required for this survey instrument.

The Likert-type scale refers to the data that respondents provide, which translated to the possible calculation of the statistical scores of the information. The original concept of the scale developed by Likert measured the objective attitudes of anonymous respondents to certain psychometric properties of the subscales, which sums up to the exploratory factor analysis or confirmatory factor analysis in testing both theories and construct validities (Ivanov et al., 2018; Leon-Mantero et al., 2020; Michalopoulou & Symeonaki, 2017; Walsh et al., 2021). The Likert scale defines how a quantitative methodological tool collects data based on behavioral measurements (Bougie & Sekaran, 2020; Pescaroli et al., 2020). One of the important goals of the Likert scale is that surveys allow participants to critically thinking of the questions, and bring their own experiences to bare while responding to each question, leading to a learning path, shared trust, and professional growth by each respondent. The research survey will include Likert-type scale responses to each question using Wu et al.'s questionnaires. Wu et al. (2020) have responses to 52 questions ranging from 1 (*strongly disagree*) and 5 (*strongly agree*) on a 5-point Likert-type scale. Simms et al. (2019) explained that there are no additional benefits in scales larger than six options because any increase in the number of scales creates participant confusion and scale wording responses namely strongly disagree as opposed to very strongly disagree. The Wu et al. scales included 1 = *strongly disagree*, 2

= *disagree*, 3 = *neither agree nor disagree*, 4 = *agree*, 5 = *strongly agree*. When the Likert-type scale value is large, a higher degree of strength and confidence is realized in competitive advantage, resulting in SMEs executives and managers utilizing SD and AC systems to transform the organization into a digital company, part of a CA strategy.

Data Collection Technique

I conducted an online survey using SurveyMonkey to collect data in order to ensure the safety of all participants. With internet connectivity, participants provided data through multiple avenues, whether online or through a smartphone or web kiosk, especially during the COVID-19 pandemic, which was a reality of research during the pandemic crisis (Mouchantaf, 2020). Bougie and Sekaran (2020) confirmed that the repeatability, dependability, and consistency of reliable instrumentation provides trust in the results, which leads to fewer errors and limits inconsistencies during the data collection. Within quantitative research, SurveyMonkey, a survey tool processes participants' data collection through a methodological format ensuring the reliability and viability of the data's quality and analysis of the information presented to researchers (Otero Varela et al., 2021; Sipes et al., 2020). The data collection was an integral part of my study, where the collected information was analyzed, processed, and evaluated to determine if a phenomenon had occurred in nature or related to a preexisting theory. Data collection permits the researcher to examine the relationships between multiple variables, emphasizing data transparency and data integrity, while conducting survey safety and ethics of participant's involvement during a pandemic.

There are advantages and disadvantages of conducting data collection through an online survey. Ball (2019) explained that there are additional advantages of data collection, especially online: (a) the expedient diffusion of the survey's reach, (b) flexibility, and (c) automation, and (d) removal of cumbersome paper-based surveys. Mouchantaf (2020) reinforced that most participants during the coronavirus 2019 pandemic could instead fill the survey online regardless of location, reinforcing their safety and permitting ease of use. K. L. Walker (2016) wrote that transparency is about knowledge and data, made available to all respondents without a hidden agenda or authoritative restriction to its content or context among both internal and external stakeholders. For instance, data collection utilizing an online survey, helps to ensure inclusivity in the data process, 24/7 availability to participants, and ease of access to online survey portal, ultimately providing a broader range of certainty in the information and reducing data errors (Rees-Punia et al., 2020; Sipes et al., 2020). There are also disadvantages of conducting data collection: (a) lack of time; (b) data distortion, information bias, and knowledge concealment; (c) no immediate follow-up questions; and (d) accumulation of biased responses in the data (Ball, 2019; Gardner, 2019; Turilli & Floridi, 2009). Fischer and Kleen (2021) provided additional challenges of data collection to include lack of proper mobile internet connection, potential data loss, and lack of understanding by multilingual and multibackground participants of the research questions. The data collection performed by the researcher demonstrates how quick, concise, and reliable research with multiple participants can be while taking a questionnaire during a crisis and what actions or inactions the researcher can take to address severe survey issue that can be vital to completing a well-documented and trustworthy research. Data collection will be critical to any reader because it informs them about the origins of the information, the source's credibility, and researcher's trustworthiness.

Though there are advantages and disadvantages cited about data collection, participants must understand their role in the research through the collection process while using SurveyMonkey. For this reason, the data collection included a letter of invitation with clear instructions about the process, usage, security, and privacy of the research data collected from the participant (see Appendices E and F). I utilized SurveyMonkey to collect the necessary data from SME manufacturing senior executives and managers in the United States. The SME participants aligned with the population sample boundaries for this research study.

Data Analysis

The research question is: What is the relationship between SD, AC, and CA? The hypotheses were as follows:

H_0: There is no statistically significant relationship between SD, AC, and CA.

H_1: There is a statistically significant relationship between SD, AC, and CA.

I conducted a multiple regression analyzing the statistical data from this study. Multiple regression is a statistical analysis conducted to gain insight among predictor variables and their relational estimates (Lien et al., 2021; Pedraza-Rodríguez et al., 2021), valued as an ambivalent tool for research and statistical inference (Snell, 2020), and decreased the misinterpretation risks from any omitted factors (Pedraza-Rodríguez et al., 2021). The data analysis will be part of a multilayered methodology within this research. The goal was to understand the outcome of the data in its totality and holistic approach towards the research question. Because there is not an infinite amount of time to go through an entire population, the inference made on a study's sample allows for the projection of the statistical outcome of the data. Comparing predictors justifies using multiple regression to determine a statistical outcome when defining which predictor is stronger (Murrah, 2020). The criterion variable in this study is competitive advantage, which has an ordinal level of measurement. The predictor variables in this study are SD and AC, which have ordinal measurement levels. Nonparametric simple regression analysis was not feasible for this research because this study involved a quantitative response variable and two predictor variables (Fox, 2000; Tanti et al., 2020). I analyzed the collected survey data and conduct a multiple linear regression (MLR) analysis for this study.

Analysis of variance (ANOVA) and simple linear regression are two quantitative statistics; it will not suffice for this study. ANOVA is a method widely used for testing the statistical significance of three or more independent groups with no main effects and no interactions while ensuring a similar sample size to determine Gaussian and omnibus tests (Frane, 2021; Mayer & Thoemmes, 2019; Mishra et al., 2019). Researchers conduct division of groups using ANOVA to find the mean through between-group variances and within-group variances (Mayer & Thoemmes, 2019), which is not part of this study. For simple linear regression, the objective is to predict the outcome of a single dependent variable centered on two different assumptions, independence and equality of variance, to determine the independent variable value (Aslan, 2018; H. Kim, 2019). The use of simple linear regression for this study was both distinct and irrelevant. This study examined two independent variables, SD and AC, and one dependent variable, CA, resulting in the acceptable use of a MLR analysis.

Assumptions

MLR consists of the parametric technique, where it is vital to understand the variable relationships. Researchers understand how to operationalize their constructs given certain assumptions while minimizing their errors. Statistical data carries a set of assumptions that account for its totality within parametric testing, especially when dealing with multiple regression analysis, which consists of four underlying assumptions (Chung et al., 2020; Hu & Plonsky, 2021). Salkind (2010) stated that parametric analysis infers what has occurred in a sample to a population, where parametric includes assumptions based on random sampling, while nonparametric does not include assumptions. I randomly selected SME manufacturing senior executives and managers who resided in the United States. Black (2004) wrote that parametric analysis is both continuous data and the normal distribution of groups. A nonparametric analysis is nominal data based on the data frequencies in categories, ordinal data, and non-distributive data incurs a Type II error than a parametric analysis (Black, 2004). Researchers test their assumptions when trying to validate the practicality of using multiple regression in a statistical analysis, which includes: (a) linearity, (b) homoscedasticity, (c) multicollinearity, and (d) normality (Chung et al., 2020; Kong et al., 2019; Olvera Astivia & Kroc, 2019). Salkind cautioned that the wrong statistical approach increases the likelihood of the outcome being unsuitable, erroneous, and improper in understanding the phenomena's occurrence. The subsequent paragraphs will highlight how each assumption affected the multiple regression analysis within this study’s given parametric statistical test.

Linearity and Homoscedasticity

In this subsection, I discuss the two assumptions, linearity and homoscedasticity, and their importance to the study. In business research, multiple regression analysis began with the conceptual model developed by a researcher in the early stage of the research process, which allowed multiple independent variables to explain the variances in the dependent variable and deepen the relationship among predictors and criteria (Bougie & Sekaran, 2020; Ionescu & Iliescu, 2021). Any effort to model the statistical relationship between SD, AC, and CA without careful consideration of other factors affected the CA elements through the following assumptions, linearity and homoscedasticity, perhaps diminishing the statistical problem and omitting the variables biases.

The first assumption was linearity. Linearity defines the computational practicality and direct analysis of quantitative variables through the goodness of fit in regression analysis (Chen et al., 2021; Ekwaru & Veugelers, 2018; Kuhfeld & Soland, 2021). Since this was a non-experimental research study, there was no baseline for the research to start from as a foundation for comparison as a controlling factor. Ionescu and Iliescu (2021) stated that the assumption of nonexperimental research is that any quantitative deviations found within the variables reduce information loss, allow precision, and account for population growth relative to its size. If the assumption resulted in a non-violated and non-curvilinear pattern, then the proof within the linear equation determined linearity (Bond, 2019; Chen et al., 2021). A positive or negative linearity result must be determined to ensure the construction of a good fit line model that can be applied to other non-experimental research studies. This allows researchers to better understand how this BD, ML, and AI model involving the manufacturing industry can apply to other similar industries.

The second assumption was homoscedasticity. Although linearity was equally distributed, the homoscedasticity assumption referred to examining the standardized residual distribution and placed evidential validity of its impact on linear regression (Kong et al., 2019; Yang et al., 2019). Regardless of how large the sample size of a study, homoscedasticity remains difficult to isolate in any statistical research model with equally scattered values from the estimated regression line and requires a stabilized variance for the analytic model to provide value to researchers (D. K. Lee, 2020; Schmidt & Finan, 2018). Homoscedasticity ensures that the singular study can be evaluated to determine if there is a significant violation through inferential understanding of the relationship between multiple variable constructs. This can be determined by understanding the descriptive statistical and inferential results of the data analysis, where data errors must be tested if they meet data reliability and validity.

Multicollinearity

The third assumption was multicollinearity. Multicollinearity denoted the coefficient estimates in the multiple regression analysis that suffer from accurate data approximation being unreliable, unbalanced standard errors, and the expected presence of outliers (Guan & Zhao, 2020; Hui et al., 2020). A chief concern of statistical analysis is the centering of a regression model and multicollinearity, where centering is a viable tool between predictors and criteria. Graphical representation of the variables determines symmetry, and the presence of nonclustering will occur in the data (Olvera Astivia & Kroc, 2019). For the data accuracy of the study, multicollinearity determines if any residual errors hinder or support the study through the variable's interactions and correlation among each other. Though it was a concern, multicollinearity ensured clarity of the variables and detected any ingenuous violations that may have harmed the research's outcomes.

Normality

The fourth and last assumption was normality. Normality defined the inspection of the residual distribution reliant on the regression errors, sample size, and the distribution of the predictors (Knief & Forstmeier, 2021), SD and AC. Kolkiewicz et al. (2021) explained that the normality assumption allows for the calculation and validation of complex functional data and high-dimensional constructs based on two characteristics, the goodness-of-fit test and the non-Gaussianity measure. Schmidt and Finan (2018) stated that violations of normality are common within linear regression models dealing with large sample size settings. The normality test weighed the sample size against Type I and Type II errors, determining how the collected data supported and satisfied the parametric assumptions during hypothesis testing (T. K. Kim & Park, 2019). Perfect multicollinearity would be uncommon and rare; there is no perfect linear normality and equidistant data between any two independent variables (Bougie & Sekaran, 2020). It was essential to detect the varying assumptions mentioned because the interpretation of the data reflected real-world data. I completed a multiple regression analysis to determine any parametric-testing violations based on these four assumptions within the research study.

Study Validity

The research study validity required that the selected instrumentation and defined data analysis mature the study's concept through the operationalized constructs, SD, AC, and CA. The research validity determined how the statistical data meets the principled assumptions, as transparency for readers and oversight for any potential violations as crucial considerations for the study (Hu & Plonsky, 2021). The scale-based construct processed unequal measurements and contaminated factors through randomization results in an even spread of these disparities across the randomized cause-and-effect relationship questioned within any research (Bougie & Sekaran, 2020). The validity of a research study can involve establishing a consistent construct measurement process through a unified standard towards empirical theories and flexible methodologies (L. D. Walker, 2020). The degree to which both theory and evidence can support different outcomes results in validity construct-irrelevant variances, invalidating how each construct interpretation will demonstrate different psychometric properties (Gómez-Benito et al., 2018). All statistical concepts associate one or more assumptions as part of their data analysis, resulting in any failure to check preliminary statistical analysis as a threat to the internal and external validity of the study (Garavan et al., 2019; Hu & Plonsky, 2021).

The process of the study validity assessed both accuracy and quality to ensure a proper and robust measurement tool. Because it is an estimation towards the truth, the study validity requires an examination as to the causation of a phenomenon for there are many reasons apart from the stated variable why a situation occurred.

Internal Validity

Internal validity is about the operational integrity of generalized variables to determine their predefined tolerance levels which can be exported to other external constructs of an environment. Internal validity projects a cause-and-effect relationship between two variables generalizable to other populations outside the study (Urban & van Eeden-Moorefield, 2018). A correlational design was associated with this study. Taylor (2013) stated that statistical data highlighted exploratory reasons to depict a logical and justified attribution of the current phenomena in nature by conducting a correlational design. Internal validity ensures the data inquiry and analysis test the goodness of measures (Bougie & Sekaran, 2020). Internal validity is attributable to the identified variables within a study under three types of validity: (a) content validity, (b) criterion-related validity, and (c) construct validity (Bougie & Sekaran, 2020; Taylor, 2013). Artvinli and Demir (2018) explained that the content validity attested by a group of experts certifies the instrumentation measures through the recognition of the representative scale items to develop the concept. Face validity does accompany content validity to ensure that the measurement in the survey through the origins of the instrumentation complements facts by robust professionals and experts (Barnoux et al., 2020; Bougie & Sekaran, 2020; Yusoff, 2019).

Criterion-related validity defines the logical justification of criterion variables, despite biasing contextual factors, to validate the concurrent and predictive correlation among construct variables, similar to the specific scaled-based measures in the assessment (Bougie & Sekaran, 2020; Cooper et al., 2019; Weekley et al., 2019). Construct validity refers to the evidentiary content of the construct to fit the goodness of measures by determining the correlative scores of the construct and matching the constructs to specified theories in a study (Grimley, 2019; Stone, 2019). To improve internal validity, researchers require randomized control of participants using selection criteria and conditional assessments of any potential inferences (Fredericks et al., 2019). Through an in-depth understanding of the internal validity's components (content, criterion-related, and construct validities), research validity will hold intact by mitigating contextual bias factors and ensuring statistical correlations within the intended variables of this quantitative research.

External Validity

Bougie and Sekaran (2020) posited that external validity concerns the generalizability of variables from one instrument to other populations. The reproduction of an instruments' outcome used in external environments with a different population and demographic characteristics allows external validity to exist within other observable studies (Fell et al., 2020; Fredericks et al., 2019). I mitigated any concerns on external validity through a specified study proposition, hypothesis, and construct variables, which permitted generalization to external populations. The construct variables, SD, AC, and CA, represented the ability to generalize each characteristic to varying SMEs, aside from the manufacturing industry. External validity relates to applied research where the primary objectives are taking the findings' generalizability towards action recommendations and multiple geographic localities (Fell et al., 2020; Malizia & Motoyama, 2019). There are threats to external validity, which apply to factors that can reduce the generalization of key constructs to a larger population or limit the advancement of knowledge necessary for critical inquiries (Hayes-Larson et al., 2019; Klink & Smith, 2001). For this quantitative study, I addressed the research purpose and any issues with external validity to explain the research intentions and significance to SME executives and managers in the United States.

Transition and Summary

In Section 2, I began with a restatement of the purpose, explained the role of the researcher and participants, highlighted the importance of the research design and method while applying it to the right population and sampling group. Next, I emphasized the significance of ethics, the study's instrumentation, and data collection strategy within this study. Then, the explanation of the study's validity presented an opportunity to explain both the internal and external rationality of the study.

Section 3 will comprise a presentation of the findings, their applications to professional practice, and the implications for social change. There will be a section on recommendations for action and recommendations for research. Next, I will provide a section known as reflections that examined what I have learned from my study. Lastly, the conclusion of the study described the relationships of the three primary constructs, SD, AC, and CA.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA. The study showed that positive social change can occur when executives and managers work to enhance and embrace human-machine teaming (HMT) in BDA and manufacturing to support a firm's competitiveness over time. The first independent variable was SD, which consisted of two subdomains, relational embeddedness and learning orientation, with six predictor variables: (a) strong ties, (b) trust, (c) shared system, (d) commitment to learning, (e) shared vision, and (f) open-mindedness. The second independent variable was AC, which comprised two subdomains, potential AC and realized AC, with four predictor variables: (a) acquisition, (b) assimilation, (c) transformation, and (d) application. The dependent variable was CA, which included three criteria: (a) differentiation advantage, (b) cost advantage, and (c) institutional advantage. The null hypothesis was that there is no statistically significant relationship between SD, AC, and CA, while the alternative hypothesis was that there is a statistically significant relationship between SD, AC, and CA. Based on the current results, SD and AC significantly predicted CA, so I rejected the null hypothesis.

Presentation of the Findings

In this subsection, I present the deviation I made from my original plan for the study, descriptive statistics, the evaluation of statistical assumptions, inferential statistics results, analysis summary, and a theoretical discussion on the findings. The current version of SPSS was used to test the violation of the study's assumptions. The following subsections also contain the statistical outcomes, tables, and figures that correspond to each evaluation of the assumption violations during the MLR examination. To address the possible influence of assumption violations, I used bootstrapping by means of 2,000 samples, resulting in a 95% confidence interval when bootstrapping is suitable.

Deviation From the Plan

As a new entrant to manufacturing, I researched the state of the manufacturing industry 2 years prior to starting my doctoral program in 2019. It was amazing to me to see the inconsistencies in productivity, labor, material costs, and overhead costs shift frequently as the U.S. manufacturing economy withered slowly because of globalization, labor costs, and advanced manufacturing incentives for a few decades. With the economic and pandemic crises of 2008 and 2022, respectively, taking place, the global environment has never been on shakier ground since the 1990s. Organizations are slowly bringing manufacturing back to the United States with multiple investments going back into rural communities. Originally, my projected plan for this study was to obtain survey responses from a well-known manufacturing association in the United States. This was in order to get access to some SME company executives and managers who may be based, have relocated, or are thinking of relocating to Austin, Texas and fall under NAICS 334 that has 30 different submanufacturing industries associated with communications, computers, electronics, and semiconductors. There were three deviations that occurred within the study that are worth mentioning to capture my experience as a researcher: (a) the impact of only using 66 responses versus 68 as originally planned; (b) being denied the ability to survey its members by a manufacturing association after a 6-week attempt; and (c) receiving only four responses from social media (i.e., LinkedIn).

First, my original plan was to use 68 participants. I calculated the sample size using the G*Power Version 3.1.9.4. to arrive at this specific number. I planned on using the instrument to survey a total of more than 68 participants who shared the qualities of being an SME manufacturing executive and/or manager; having management or IS experiences in the last 5 years; using AI, ML, or BD in the last 5 years; and classifying their industry within NAICS 334. I was unsuccessful in both trying to conduct the survey through a manufacturing association or ask for voluntary participation within LinkedIn. I had sent my survey through a manufacturing association but failed to get any results. I received permission to attempt on recruiting participants through social media focusing on LinkedIn. I endeavored to get professional assistance recruiting through LinkedIn, but this failed as well, resulting in only four participants taking the survey after multiple tries. After the multiple attempts described in the subsequent paragraphs, I resorted to using SurveyMonkey's built-in capabilities to recruit participants and get the permission necessary from the Walden University IRB to use random participants for the study. The total came out to 66 respondents (i.e., 62 from SurveyMonkey and four from LinkedIn). The 66 participants did not affect the study's outcomes like 68 participants would have because of bootstrapping, which does not affect the final outcomes of the data analysis for the study.

The survey responses I would have collected from this association could have been fruitful in understanding their quantitative value for strong management, BD, AI, ML, and competitive cost strategies to compete in a realignment of the global business manufacturing market. I attempted to contact the association for about 8 weeks, both emailing and calling them numerous times. In the 8th week, I received an email discussing the inappropriateness of the association asking its members to respond to any survey. I thanked them for taking the time to read my email request and providing me with a response about surveying their members. I immediately stopped all contact and moved on to another avenue to collect this information.

The latitude given to attempt a social media survey through LinkedIn afforded me the opportunity to get a variety of respondents in different IS career fields that are focused on AI, ML, and BD. While granted permission by the Walden University IRB to use this medium, unfortunately, after multiple attempts to have varying groups and communities participate in the survey, there were only four participants after a 2.5-month attempt. These four participants were part of the large collection effort to get to 68 total respondents. Though this did not offer the opportunities I thought it would, it was another experience I gained as a researcher in understanding that research is hard and gets complex when it is about a personal or professional connection. I was granted permission to conduct survey collections using both mediums, LinkedIn and SurveyMonkey.

Because of the extended time period necessary to find 68 qualified participants and the extensive loss of time to find a partnering organization to work with me on this study, I was granted permission to conduct and complete the data analysis phase of the study with two fewer participants than originally required by both my chair and second committee member. This resulted in using SurveyMonkey's survey system to collect the data after 6 months of various attempts, rewrites, ethics resubmissions, and acceptance of a validated survey framework of 66 participants out of a total of 68 to be accepted as the final tally.

Descriptive Statistics

These descriptive statistics centered on analyzing the research data that were collected over a 6-month period to determine if any relationship exists between SD, AC, and CA. The response rate was 36% for the research study, with a completion rate of 100%. I distributed the survey using both SurveyMonkey and the social media platform, LinkedIn, to a total of 184 SMEs executives and managers. There were about 66 survey responses that were returned complete and focused on the United States. Approximately 64% of the survey responses were rejected because of incompletion, inconclusiveness, data error, and/or completion by nonmanufacturing SME executives and managers who did not qualify to take the survey. The results of the descriptive analysis show the means and standard deviations of the independent variables and subvariables of SD and AC and the dependent variable and subvariables of CA, which are depicted in Table 2.

Table 2

Means and Standard Deviations for Independent and Dependent Variables

Variable	*M*	*SD*
SD	3.566	.6677
AC	3.558	.6244
CA	3.439	.6530

Note. $N = 66$.

Based on the results of the data analysis, I rejected the null hypothesis and found that SD and AC had a significant positive relationship on predicting CA in the United States.

Test of Assumptions

Five principal assumptions of MLR exist where the first three are fixed effects and the last two are random effects. MLR holds the following assumptions: multicollinearity, normality, linearity, homoscedasticity, and independence of errors and outliers (Green & Salkind, 2017; Li et al., 2017). In this research study, I used SPSS Version 28 to analyze the data for this specific MLR model. I assumed that the random effects could be used to determine linearity since this was a nonexperimental study.

Multicollinearity

The multicollinearity assumption was met and tested by examining the diagnostic methodology of the variance inflation factor (VIF), tolerance, the Pearson correlation, and the correlation coefficients. Marcoulides and Raykov (2019) stated that VIF and tolerance are two frequent and relevant indices used to examine individual predictors' potential for strong contributions to near multicollinearity and interrelationship degree among explanatory variables in MLR. Gokmen et al. (2022) summarized that multicollinearity has multiple criteria that must be deduced to determine if the observable variables are error free because of misreporting by participants, data collection errors, or miscoding by collectors. In this subsection, I clarify how these observable variables are error free through the analytic resolution found in testing my assumptions annotated in Sections 1 and 2 of this study.

VIF is calculated as 1-R^2, where R^2 represents the coefficient of determination and degree of variance inflation (Gwelo, 2019; Thompson et al., 2017). VIF represents the probable collinearity that occurs among predictor and criterion variables, which can lead to standard error increases and inflated coefficient variances (Gwelo, 2019). If the variances of two explanatory variables are greater than 10, then VIF would result in a significant collinearity between the variables (García et al., 2020; Nguyen & Ng, 2020). If the collinearity of two variables is equal, then there is a perfect collinearity; if the variables are not equal, then there is a near collinearity also known as imperfect (García et al., 2020). Based on the analytic results, there is a perfect collinearity that exists between SD (VIF = 4.459) and AC (VIF = 4.459), and the variances are less than 10 (see Table 3). This represents a correlation between the predictor variables, SD and AC. Lastly, VIF can be observed because there are no problems with multicollinearity. Researchers must investigate any standard errors that may occur elsewhere in the explanatory variables. Next, it is important to examine the tolerance of the analysis. Tolerance is a function of VIF (1/VIF), where the smaller the variance of the tolerance level is, then the likelihood increases that the regression model is multicollinear (Gokmen et al., 2022; Thompson et al., 2017). If the tolerance is less than 0.10, this indicates a serious collinearity problem among the explanatory variables of a study (Marcoulides & Raykov, 2019). The tolerance of the analysis was .224 for both predictor variables of SD and AC (see Table 3). Though the tolerance is an inverse of VIF with less significance in the interpretation of the results, as a researcher, I had to consider all factors to determine if multicollinearity does or does not exist. The Pearson correlation test provides the statistical assessment between two variables that signal the direction, strength, and significance of their connections (Bougie & Sekaran, 2020). For the Pearson correlation, the scrutiny of the bivariate correlations among independent variables looks at how large R^2 is to be evidence of multicollinearity (Thompson et al., 2017). Results of the analysis illustrated in Table 3 show that SD and AC have a value of .881, indicating the variables have a positive direction, with a strong strength at 88.1%, and a positive significance between each other. The multicollinearity assumption violation was not evident. Table 3 depicts the VIF, tolerance levels, and Pearson correlation coefficient of the predictor variables.

Table 3

Multicollinearity Statistics for Criterion Variable

Variable	VIF	Tolerance	Pearson correlation
SD	4.459	.224	.881
AC	4.459	.224	.881

Note. *N* = 66.

I evaluated multicollinearity by displaying the correlation coefficients among the predictor variables. All bivariate correlations were large (see Table 4). The pairwise correlations illustrate that the criterion variable, CA, exhibits strong marginal correlations where SD (r = 0.770) and AC (r = 0.773). In this instance, because of the correlation coefficients being medium, there are likely signs that minimum multicollinearity among SD, AC, and CA exist, resulting in a linear dependence among all three variables.

Table 4

Correlation Coefficients Among Study Predictor Variables

Variable	SD	AC	CA
SD	1.00	.881	.770
AC	.881	1.00	.773
CA	.770	.773	1.00

Note. N = 66.

There are no violations of the multicollinearity assumption that are of significance existing between the predictor variables for this study.

Normality, Linearity, Homoscedasticity, Independence of Residuals, and Outliers

I assessed the normality, linearity, homoscedasticity, independence of residuals, and outliers by examining the normal probability plot (P-P) of the regression standardized residual (see Figure 2) and the scatterplots/histogram of the linearity, homoscedasticity, and standardized residuals (see Figure 3). These graphs indicated there were no major violations of these five assumptions. First, the tendency of the points to lie in a reasonably straight line (see Figure 2), diagonal from the bottom left to the top right, provides supportive evidence that the assumption of normality was normally distributed. Second, the linearity of the residuals has a straight-line relationship with the predicted CA scores. Third, the test of homoscedasticity is satisfied in this outcome because of the points being in the shape of a rectangle, demonstrating homoscedasticity (see Figure 3). Fourth, the transparent or systematic pattern in the scatterplot of the independent residuals (see Figure 3) supports the tenability of the assumptions being met. Lastly, according to Rodu and Kafadar (2022), boxplots are well-known visualization graphics that help to quickly exhibit the median, interquartile ranges, limits, and observations outside the boundaries. I tested the assumption of the outliers using the boxplot method (see Figure 4). The outliers refer to the visualization and communication of the data collected over 8 weeks. My interpretation of the boxplot (see Figure 4) is that the variables for SD and AC confirmed that no outliers were present, and the assumption was not violated.

Figure 2

Normal Probability Plot (P-P) of the Regression Standardized Residuals

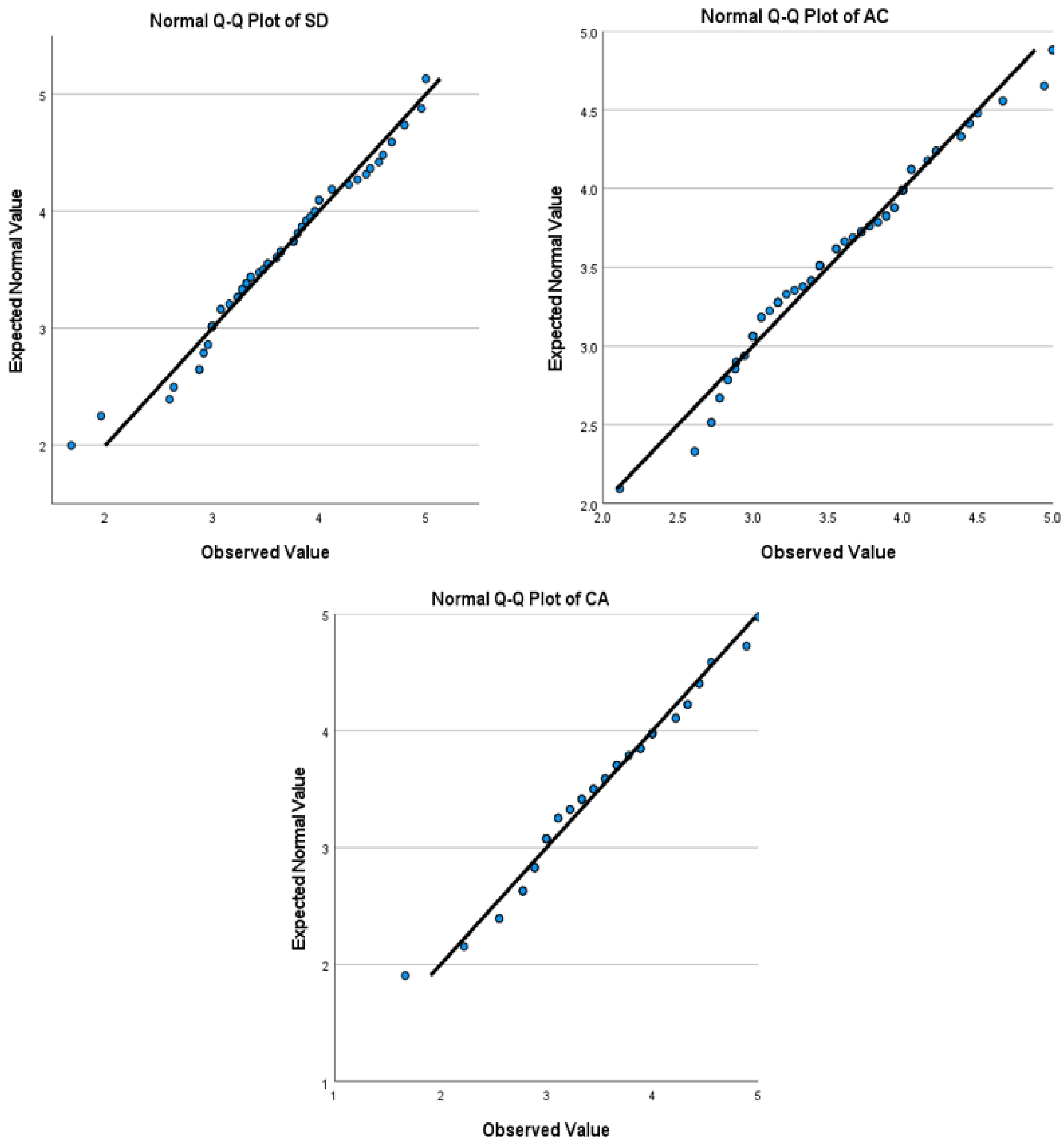
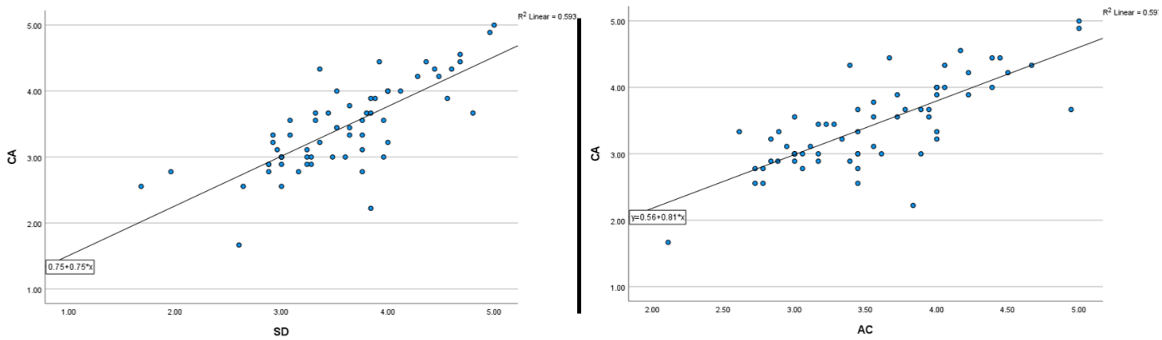


Figure 3

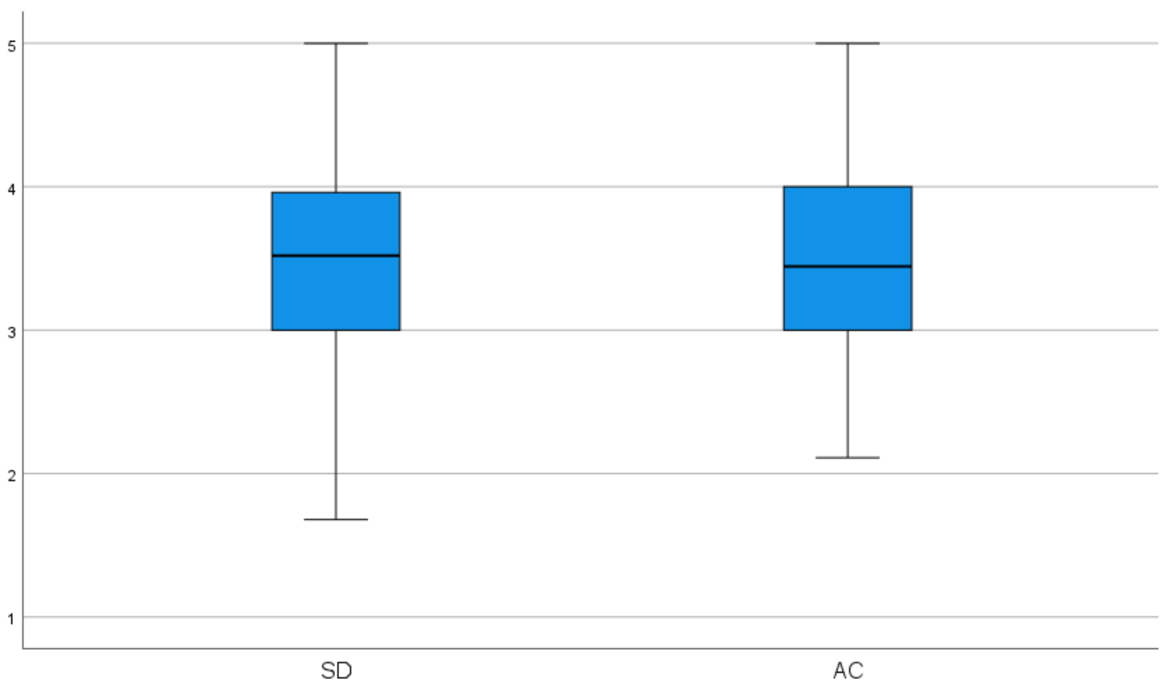
Scatterplots of the Linearity, Homoscedasticity, and Standardized Residuals



Note. Scatterplot visualization illustrates the positive direction and strength of the good fit line where the increase in both SD and AC leads to an increase in CA.

Figure 4

Boxplot of Strategic Dexterity and Absorptive Capacity



Inferential Statistics Results

I conducted standard MLR to interpret the results. MLR is an extension of the bivariate linear regression and uses the independent variables (i.e., predictors) to predict the outcomes within the dependent variables (i.e., criteria) through a fitted-linear analysis while minimizing the inaccuracies (Bougie & Sekaran, 2020). Standard MLR, $\alpha = .05$ (two-tailed) was used to examine the efficacy of SD and AC (i.e., the independent variables) in predicting CA (i.e., the dependent variable). The totality of the quantitative research design allowed me to better understand what measures needed to be taken to complete the research study on time and answer the research question thoroughly. The research question was: What is the relationship between SD, AC, and CA? The null hypothesis was that SD and AC would not significantly predict CA. The alternative hypothesis was that SD and AC would significantly predict CA. The sample size consisted of 66 executives and managers equally represented across the public, private, and nonprofit sectors. The vital point of MLR is to understand the data set associations where the best-fit line is necessary to minimize residual errors and the specified constructs can be operationalized against a given phenomenon (Nhung et al., 2022).

The standard MLR was performed using SPSS Version 28 to answer my research question. Preliminary analyses were conducted to assess whether the assumptions of multicollinearity, outliers, normality, linearity, homoscedasticity, and independence of residuals were met. A significant and meaningful relationship was identified between strategic dexterity, absorptive capacity, and competitive advantage, where the $F(2, 63) = 54.29$, $p = .001$, $r^2 = .63$ (see Table 5). Since this was the first test type performed in the

United States, the research study was deemed exploratory in nature, where the confidence level was at 95% (i.e., $\alpha = .05$). It is estimated that 63% of the variation in competitive advantage was accounted for by the linear combination of the independent variables, SD and AC (see Table 6). In the analysis, under the model summary (see Table 6), $r = 0.795$, which implies a moderate correlation that the linear combination of SD and AC perfectly predict CA. The final model, CA, was significantly correlated with AC (*beta* = .439, *p* = .011) and with SD (*beta* = .391, *p* = .016) in this study (see Table 7). The final predictive equation was: CA = .481 + .391(SD) + .439(AC). The test concluded no serious violation of the test assumptions noted within the MLR analysis. The study results demonstrate that as levels of strategic dexterity increases and absorptive capacity surges, substantial competitive advantage is possible for executives and managers in the manufacturing sector and the communities they serve.

SD

The positive slope for SD (.391) as a predictor of CA indicated a .391 increase in CA for each point increase in SD. In other words, CA tends to increase as SD increases.

AC

The positive slope for AC (.439) as a predictor of CA indicated there was about a .439 increase in CA for each point increase in AC.

Table 5

Analysis of Variance (ANOVA)

	Model	Sum of Squares	*DF*	Mean Square	*F*	Sig.
1	Regression	17.538	2	8.769	54.285	<.001[b]
	Residual	10.177	63	.162		

	Total[a]	27.714	65

Note. $N = 66$
[a] Criterion variable: CA
[b] Predictors: (Constant), AC, SD

Table 6

Model Summary With Dependent Variable

Model	r	r^2	Adjusted r^2	Std. Error of the Estimates
1[a]	.795[a]	.633	.621	.4019

Note. $N = 66$
[a] Criterion variable: CA

Table 7

Coefficient of the Independent Variables

Variable	B	Unstandardized Coefficients Std. Error	Standardized Coefficients *Beta*	t	*Sig.*
1 (Constant) [a]	.481	.290		1.656	.103
SD	.391	.158	.400	2.482	.016
AC	.439	.169	.420	2.606	.011

Note. $N = 66$
[a] Criterion variable: CA

Table 8

Descriptive Statistics – Outliers with Z-scores

Variable	Minimum	Maximum	Mean	Std. Deviation
SD	1.68	5.00	3.5655	.66774
AC	2.11	5.00	3.5580	.62436
CA	1.67	5.00	3.4394	.65297
Zscore(SD)	-2.82363	2.14836	.0000000	1.00000000
Zscore(AC)	-2.31737	2.30960	.0000000	1.00000000
Zscore(CA)	-2.71485	2.39000	.0000000	1.00000000
Valid N (listwise)				

Note. $N = 66$

As stated above in Table 7, each predictor at alpha = .05, where for SD, $t = 2.482$, $p < .016$ and AC, $t = 2.606$, $p < .011$. The hypothesis is rejected with the probability of rejection occurring at SD = 60% and AC = 58% respectively, and retain the alternative hypothesis that there is a statistically significant relationship between strategic dexterity, absorptive capacity, and competitive advantage.

Analysis Summary

In this subsection, I provided a summary of the statistical analysis for the research study. Data analysis is not simply causal inferences, where varying data is comparable to determine a correlational relationship, but it is a consideration of causality, correlation, and responsiveness of other factors that play a central role using specific statistical tools (Lübke et al., 2020). I selected IBM SPSS to determine the effects correlation has on the causation of the phenomena and discovered a strong correlation among the independent (SD and AC) and dependent variables (CA). When two separate variables, have a strong association as evidence of the cause of a different variable, then it adds integrity to the research study (Bailey et al., 2018). There are cases when a weak association occurs, and researchers have to suspect other areas, e.g., the level of significance chosen, magnitude of the effect size, and confounding bias. These are weak causal associations to the larger population, but it demonstrates the importance of internal validity (Bailey et al., 2018). This is because researchers are inferencing the causality to assist in providing answers to the correlation. Unlike an experiment, observable research studies need to be generalizable, regardless of its weak association, I used MLR to examine SD and AC to predict CA. Assumptions related to MLR were explored, with no serious violations noted. The model was able to predict CA significantly, $F(2) = 54.29$, $p < .001$ (see Table 5). Both independent variables, SD and AC ($p < .05$) were statistically significant predictors of an organization gaining a CA.

Within the study, there were no outliers identified as part of the analysis (see Figure 4). An exploratory data analysis of the study deals with nonparametric methods to help understand the data and identify any ambiguous trends (Lewandowski & Bolt, 2022). We can expand our understanding of this through the normality and assumptions of outliers and their values through a random sample of the survey to be taken as the deterministic value of a given population. The graphical illustration of the box plots used depicted no outliers as shown in Figure 4. We exploit the findings in Table 8 of the z score. The z score has a standard deviation of 1 and mean value of 0, which help to normalize any residual errors in the data (Abdi & Williams, 2022; Richard, 2022). In Table 8, I added the z score table to show no outliers in the data exist, comparing the mean and standard deviation of 0 and 1 respectively. There was no abnormality within the data points.

Theoretical Discussion on Findings

The findings indicated that the relationship between strategic dexterity and absorptive capacity as a statistically significant predictor of CA, $F(2) = 54.29$, $p < .001$), which supports Teece et al.’s (1997) DCV theory, and the relevance and suitability of the theory towards competitive advantage. Teece et al. stated that the central inquiry for organizations seeking an understanding of adaptive and active strategic management, is how SMEs endure and attain competitive advantage over time through the development of DCV theory. Because of the rapid pace of technological innovations within society, manufacturing executives and managers must continually keep pace with the latest emerging technologies in BD, AI, and ML in order to gain a competitive advantage. DCV theory takes into account both internal and external environment factors that could affect company performance, while shifting the paradigm towards approaches in strategic interactions, defensible competitive forces, and protective in-capital resources for organizational competitive successes (Gonyora et al., 2022; Mikalef et al., 2019; Teece et al., 1997). For this reason, Teece et al. described DCV as an essential foundation for organizations for the following reasons: (a) to compete in timely reactions to market growths and complications and (b) make near-real time data available for decision makers through sensemaking of the numerous sensors within the manufacturing assemblies to support organizational competitiveness. SME manufacturing executives and managers can apply the DCV theory as a framework towards understanding which path dependencies and digital assets are necessary for their firms to remain competitive, determining how to position their manufacturing products to gain market advantage, and defining how best to amalgamate, shape, and reconstruct both internal and external competences to address an ever-changing business landscape.

Resource exploration is critical for managers to discover their hidden assets and capabilities to compete dynamically in a broad business market. The DCV theory describes how a firm can conduct strategy adroitness at the forefront of an organization's functional capabilities, where managers take risks and prudent actions towards creating an organic CA (Dubey et al., 2019; Teece et al., 1997). Managers with autonomy can leverage untapped potential through the trust placed on them by stakeholders and employees looking to advance the strategic nature of the organization. The DCV theory acts as an innovative bridge for SMEs to determine the governing structure of its workforce architecture and the business decision-making strategic system to employ in the organization as found within the study. The digital transformation of today's companies must take mundane tasks away from employees, permitting organizational leaders to focus on increased operations, which leads to faster adoption and BD creativity towards new products or services and a true competitive advantage (Leavy, 2020). Lin et al. (2020) stated that managers trusted by their organization with greater executive power thrive in environmental uncertainty, leading to confidence in resource allocations, rapport with external industry partners, and greater decision-making capacities to set the right direction for the company. DCV tenets stress the importance of how a business manager creatively capitalizes on the exploratory competitiveness of the firm based on its strengths and opportunities for potential future business growth. The advantage of having a manager focused on a firm may be that it elevates the business conversation about exploiting those resources and capabilities to strengthen its competitiveness.

Applications to Professional Practice

The purpose of this quantitative correlational study was to examine the relationship between SD, AC, and CA in the United States. SME manufacturing leaders and managers will find the results of the study applicable to their industry, where mutual trust and shared understanding of managers are vital to support BD and AI/ML algorithms. SMEs should value BD as a strategic asset for their organization, ensuring it aligns to their data strategy, organizational culture, executive and managerial administrative roles, and decision-making culture throughout the enterprise (Kugler & Plank, 2022). This study demonstrated that an applicable BD and AI/ML blueprint for SME manufacturing ecosystems exists in the relationships between SD, AC, and CA during times of great societal shock and uncertainty, namely COVID-19. A key factor in aiding SME leaders to understand the dynamic nature of their industry is data, while investing in both intangible and tangible resources to be agile, distinct, and competitive (Behl, 2022; Munir et al., 2022). SMEs can enhance the decision advantage for executives and managers by establishing a competitive data and ML roadmap for 1–5 years, creating opportunities for the flourishment of employees' education and training opportunities, and developing new innovative IT tools and capabilities within their manufacturing ecosystem.

The specific business problem is that some SME manufacturing senior executives and managers do not know whether a relationship exists between SD, AC, and CA. Based on this study, I can confirm that such a relationship exists that is positive in their interrelationships and the interdependences of the predictor (SD and AC) and criterion (CA) variables for SME manufacturing organizations. The digital transformation in manufacturing is part of an evolutionary continuum with defined standard operating procedures, mature policies, BD sets, and key manufacturing practices, essential to not only codify organizational knowledge, but increase innovation and competitiveness along with absorptive capacity internally and externally for SMEs to thrive long-term (Shah, 2022). Because this study has demonstrated that SD and AC are statistically predictors of

CA, much of the specific business problem statement are valid. Based on the findings of this research, SME manufacturing senior executives and managers should examine ways that enable them to increase their SD and AC levels through differentiating their AI/ML product offerings and portfolios, while assessing cost advantages through economics of scale using high-quality competitive data sets to reduce cost expenses.

Implications for Social Change

The changing landscape of manufacturing demonstrates the need for a new digital engine that supports communities once devastated by organizational departures, signifying an industry evolution taking place amongst the new digital economy where the needs and consumption of society service towards cloud, sustainability, BD, and automation. Villegas et al. (2007) explained that the purpose of social change in research is to act as a dialogue among researchers and other active stakeholders on the development of concrete actions, steps, and advocacy works that can be carried out to bring change in society. With increased focus on engineering process to aid manufacturers, clients and civil society are better supported through numerous cloud solutions, AI/ML innovations, and digital transformation, which help integrate disparate devices and platforms together for business operations in local communities (Nti et al., 2022). Sustainable additive manufacturing demonstrates three key principles, social, economic, and environmental, focused on the human aspect of manufacturing, where executives and managers can start to reduce their carbon footprint, and replace it with stronger quality materials utilizing AI/ML and BD towards data-driven manufacturing (T. Li & Yeo, 2021). This transformation facilitates the importance of HMT on the factory floors, reassures employees of better life-work balance, helps to upskill the workforce, automates future model developments, improves workforce collaboration, and integrates various functional units, all supporting the communities they serve (Ulas, 2019). The positive social change can be viewed as economy mobility of wage workers to higher wages, support to high quality goods, and upskill and training in the new century of digital manufacturing.

Within manufacturing, employees must be the beneficiaries of the social digital change, where the perceptions must match the actions of employers towards employing successful AI/ML, cloud, and BD strategies that lead to successful business practices. Though today's employee contracts may not explicitly support career progressions in AI/ML manufacturing centers, the relationship between employees and organizations may start the social relationship dynamics of the goodwill of executive and managers to support their employee's long-term growth (Lu et al., 2019). In the literature review, I discussed the transformative nature of AI/ML and its persistent presence in manufacturing and society. The increased frequency of smart manufacturing and intelligence manufacturing explores the notion of using cyber-physical systems, cloud, AI/ML, and BD to support human knowledge, experiences, and critical thinking towards resolving complex enterprise challenges (Sharma & Villányi, 2022; Yao et al., 2017). Multiple manufacturing industries will evolve depending on sustainability practices and models that help to advance human society, yet ensure differentiate pricing and cost advantages, good quality purchases, and greater profit margins for executives and managers. Human cognition and logic are necessary for a manufacturing organization to survive. Likewise, the workforce must buy into the strategy that not only advances AI/ML, BD, and cloud, but that it serves the communities' interest for the long term.

Recommendations for Action

In this study, the findings showed that SD and AC were statistically significant predictors of CA. Executives and managers should interpret the results as a call to action to reinvigorate SME manufacturing at an accelerated rate, instituting a culture of trust, innovation, and digital upskilling, centered in the middle of HMT. SME manufacturers should view digital transformation as an opportunity to use AI and BD to reinvigorate business operational models, change the consumer-business digital paradigm, create personalized services for customers, and optimize business experiences, towards competitive advantage (Grover et al., 2022). Another area of consideration is the data standardization that must occur to seamlessly have disparate data sources communicate with each other, to give a concrete, timely, and actionable wisdom for an executive or manager to act upon. To clarify, SME manufacturing organizations can take action to institute knowledge graph, decomposed data objects from the original data sources that allow machine-to-machine translation to occur. Data science teams can apply AI, ML, and DL to calculate various algorithms to get to predictive analytics, inquisitive analytics, preventive analytics, prescriptive analytics, and descriptive analytics (Abu-Rasheed et al., 2022). SME manufacturing organizations are beginning to see fruitful benefits on a small scale with the introduction of HMT as a central component along with BD, absorptive capacity, AI/ML, and cloud to support future manufacturing development. This will be fundamentally important for SME manufacturers to consider in their daily operational models.

Recommendations for Further Research

The objective of the study was to examine the relationship between SD, AC, and CA. A limitation of my study was on my inexperience of as a novice researcher in completing a study. Because the manufacturing community is based on trust, reputations, and knowledge of the industry, the infusion of AI, ML, and data may not be trustworthy yet in many institutions, resulting in a lack of understanding about how best to phrase the structure and questions of the survey. I recommend additional research include partnering with an experienced manufacturing expert knowledgeable about the technology used on the manufacturing floor and starting with a qualitative survey to build trust with executives and supervisors in the manufacturing business community prior to sending out quantitative surveys.

The second recommendation for future research is to narrow the field of questions out to the manufacturing business community from 56 to 23 questions. On average, it took executives and supervisors about 10 minutes to complete the survey. The less time spent on the survey the better; the word of mouth could have been in reaching more participants. In the future, it would be best to streamline the questions for an average of 5-6 minutes to take the entire survey. The last recommendation for future research is to examine the geographic selection of SME executives and managers within manufacturing using machine learning across the global. The digital economy will not only affect the United States, but it has a large impact on the world. Similar to the airplane, which shaped transportation of goods and services, the power of AI, ML, and BD will shape how ecommerce, manufacturing, retail, logistics, space, and broader digital market, functions with its environment in the larger global market.

Reflections

The doctoral study journey is a challenging endeavor that required me to step away from other researchers' works and focus on my own relevant research topic that can support many communities and businesses who want to better explore, examine, and understand BD, ML, and AI in an ever-changing and complex business environment. This was especially true in my interest of the manufacturing industry that has been battered and plagued with globalization, loss of jobs, skills/training shortages, and productivity disruptions. Researchers have come to appreciate the unembellished and factual understanding of a doctoral study while pursuing a life-long goal. As a student of higher education for over 20 years, my interest has been to know if SME manufacturing executives and managers' SD attributes along with AC in-depth orchestration of data analytics, can lead organizations toward a competitive advantage. As a military service member, manufacturing was a new dimension for me, but an area of interest that my journey has led me to better understand how businesses operate in a global environment. During the conduct of my study, I found my professional expertise and personal interest distracted me constantly, increasing the level of research bias within the study. The use of MLR helped me to compare and contrast quantitative data of my target population to remove biases predetermined about the manufacturing industry.

In my doctoral journey, I faced difficulties as a quantitative researcher that was unexpected throughout my study. My initial biases were that all manufacturing associations seek to expand their knowledge of the complex environment and welcome researchers and doctoral candidates to explore and examine how technology can support the assembly line worker or factory employee. I found that it is harder to break into the manufacturing sector to seek help or acceptance from senior association members to conduct studies that support the digital evolution of manufacturing. This led to a 6-month delay in pursuing the manufacturing association's assistance for survey participation that can benefit their members. Even, when I offered to write a summarized report with quantitative data that anonymizes their members' data and information, this was rejected. I had to rely on other venues to quickly collect data through social media or a survey platform to complete the study. It was not an easy process, yet I am fulfilled by what has transpired because I learned a lot of lessons about the state of manufacturing through my interactions, research, and in-depth reading about the digital landscape shaping the industry today and into the future. Lastly, there is more to learn about what causes competitive advantage specifically within larger manufacturing organizations, expanded production line, and data-driven production floors, the findings in this study acts a strong foundation for SME executives and managers.

Conclusion

In this quantitative study, I examined the relationship among SD, AC, and CA. This study established that SME manufacturing executives and managers SD and AC were both statistically significant predictors of CA. Both the independent variables of SD and AC were statistically significant predictors of CA. Since SD and AC justify Teece et al.'s (1997) DCV theory as a paradigm for a successful digital economy, SME manufacturing executives and managers should consider integrating, building, orchestrating, and synchronizing internal and external resource capacities, path dependencies, and market positions towards a transition into high-end digital manufacturing focused on BD, AI, and ML, as a key strategic tenants and digital assets for their organizations.

This study may be valuable to manufacturing businesses because it considers the strong adoption of BD, AI, and ML as strategic assets to advance productivity in an organization. SME manufacturing leaders have considerable interest in a future digital workforce and robust AI adoption strategies. This study could improve business practices by providing an innovative approach to the training, hiring, and reskilling of an IT workforce that can be an asset to the SMEs' long-term successes leading to high-quality designs, high manufacturing standards, improved safety records, and high customer demands of products. Change is constant in business, and social change is an ongoing discussion daily with senior executives; technology should not be used as a discriminative tool in business hiring practices, promotion boards, or bonus pools. The results might contribute to positive social change by ensuring every worker can benefit from the future of BD, ML, and AI to help their long-term careers, which helps build healthy, strong, and foundational interconnected social communities and systems.

The principal objective was to provide SME executives and manager with extensive knowledge and data analyses about how SD, AC, and CA aligned to current and future digital innovations in BD, AI, and ML leading to increase organizational competitiveness and success. Strategic enterprise leaders are always seeking the next technological catalyst that will give them an advantage and a competitive edge in business over their competitors. I pursued the doctoral study from a business perspective of how BD, AI, and ML affect the strategic calculus of business leaders who struggle to implement technology changes in their business cycle whether it is training their employees or executing complex tasks in order to compete within the uncertain and ambiguous business environment. The results of this study strongly supported Teece et al.'s (1997) DCV theory. Strategic organizations make a societal impact on future employees in the United States' workforce when they become responsible corporate citizens bound by ethics, values, and morals in unleashing the full potential of BD, AI, and ML in future Science, Technology, Engineering, and Math STEM talents across their organizations.

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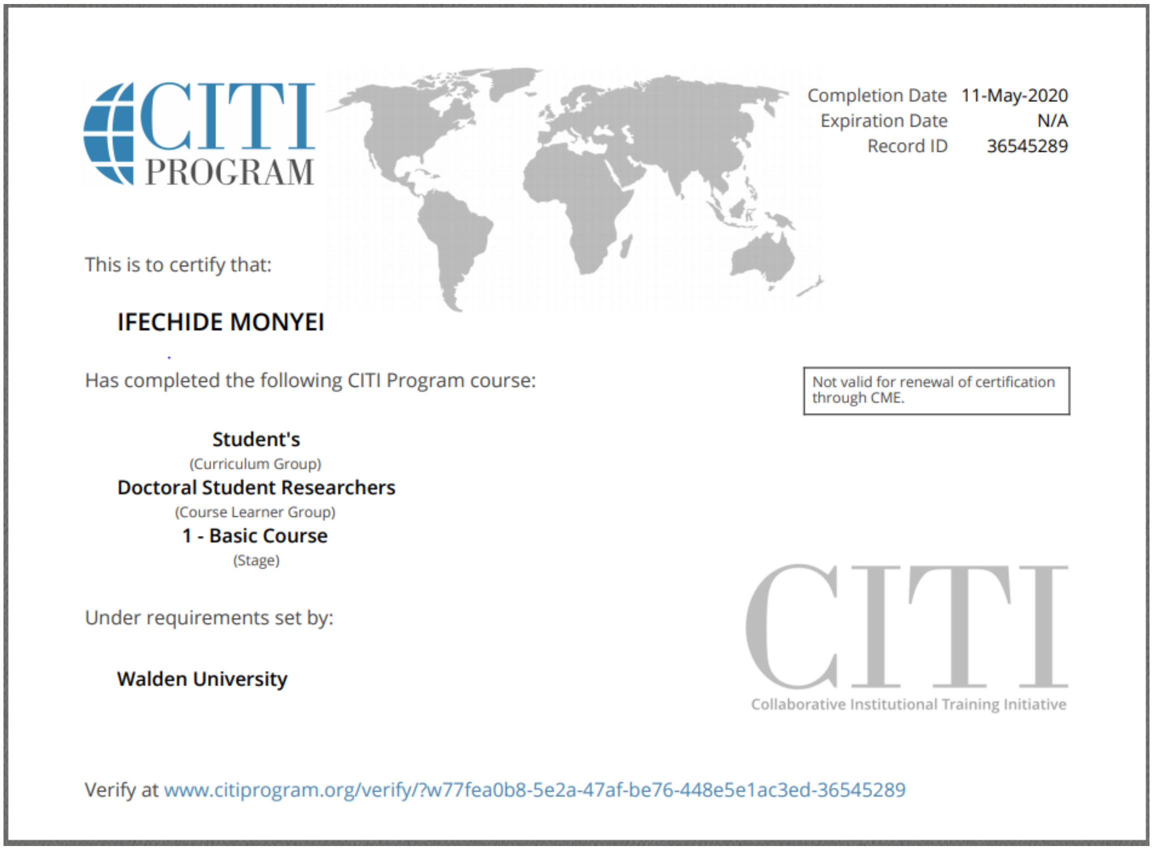
Appendix A: CITI Program – Belmont Report and Its Principles



CITI PROGRAM

Completion Date 11-May-2020
Expiration Date N/A
Record ID 36545289

This is to certify that:

IFECHIDE MONYEI

Has completed the following CITI Program course:

Not valid for renewal of certification through CME.

Student's
(Curriculum Group)
Doctoral Student Researchers
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Walden University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?w77fea0b8-5e2a-47af-be76-448e5e1ac3ed-36545289

Appendix B: Wu et al.’s (2020) Survey Instrument

Mark the appropriate selection to the following statements below by a tick (✓) to each statement. Please respond to all questions accurately. Surveys not completed will be discarded.

1. What is your industrial sector?
   - ☐ Motor manufacturing
   - ☐ Electronic parts
   - ☐ Chemicals
   - ☐ Semiconductors
   - ☐ Precision machinery
   - ☐ Information Technology
   - ☐ Other

2. What is your profitability?
   - ☐ Low profit
   - ☐ Medium profit
   - ☐ High profit

3. What is your organization’s marketing proportion to total costs?
   - ☐ <1%
   - ☐ 1-3%
   - ☐ 3-5%
   - ☐ 5-7%
   - ☐ >10%

4. What is your organization’s research & development (R&D) proportion to total costs?
   - ☐ <1%
   - ☐ 1-3%
   - ☐ 3-5%
   - ☐ 5-7%
   - ☐ >10%

5. Please indicate your level of agreement with the following statement regarding your management experiences in the transition of manufacturing sector to incorporate Big Data, Machine Learning, and Artificial Intelligence within the organization (choose the response that most closely applies to your level of agreement):

			Strongly Disagree	Disagree	Neither Agree or Disagree	Agree	Strongly Agree
Strategic Dexterity	Strong Ties	Our company received support from our domestic partners in managerial resources.					
		Our company received support from our domestic partners in emotional support.					
		Our company received support from our domestic partners in time.					
	Trust	Because of doing business for so long, our company and partners understand each other well and quickly.					
		In our contacts with domestic partners, we have never had the feeling of being misled.					
		Both sides are expected not to make demands that can seriously damage the interests of the other.					
		The strongest side is expected not to pursue its interest at all costs.					
		Informal agreements have the same significance as formal contracts.					
		Both sides know the weaknesses of the other and do not take advantage of them.					
	Shared System	The systems have been tailored to using the systems brought from domestic partners					
		The domestic partners developed specific procedures for us to follow.					
		The domestic partners have made efforts to instill its business philosophy in our managers.					
	Commitment to Learning	The sense around here is that employee learning is an investment, not an expense.					
		The basic values of this organization include learning as key to improvement.					
		Learning in my organization is seen as a key commodity necessary to guarantee organizational survival.					
		Managers basically agree that our organization's ability to learn is the key to our competitive advantage.					
	Share Vision	All employees are committed to the goals of the organization.					
		There is total agreement on our organizational vision across all levels, functions, and divisions.					
		There is a commonality of purpose in my organization.					
		Employees view themselves responsible for the direction of the organization.					
		Employees view themselves as partners in charting the direction of the organization.					

	Open-mindedness	Managers basically agree that it is important to accept diverse viewpoints.					
		We are not afraid to reflect critically on the shared assumptions we have made about our customers.					
		Our organization pays much attention to original ideas.					
		The culture in our organization emphasizes continuous innovation.					
Absorptive Capacity	Acquisition	We have the capacity to capture relevant, continuous, and up-to-date information and knowledge on current and potential competitors involving machine learning and big data.					
		There is a degree of management orientation toward waiting to see what happens within machine learning and big data, instead of concern for and orientation toward their environment to monitor trends continuously and at a wide range and to discover new opportunities to be exploited proactively.					
		The organization has taken a role in ensuring the frequency and importance of cooperation with R&D organizations on machine learning and big data - universities, business schools, technological institutes, etc., as a member or sponsor to create knowledge and innovations.					
		There is effectiveness in establishing programs oriented toward the internal development of technological acquisitions of competences from R&D centers, suppliers or customers on machine learning and big data.					
	Assimilation	We have the capacity to assimilate new technologies and innovations such as machine learning and big data that are useful or have proven potential.					
		There is the ability to use employee's level of knowledge, experience, and competencies in the assimilation of machine learning and big data, and interpretation of new knowledge.					
		There is a degree to which company employees attend and present papers on machine learning and big data at scientific conferences and congresses are integrated as lecturers at universities or business schools or receive outside staff on research attachments.					
		Our organization has attendance in training courses, trade fairs, and meetings on machine learning and big data.					
		We have the ability to develop knowledge management programs, guaranteeing the company's capacity for understanding and carefully analyzing knowledge and technology from other organizations.					

	Transformation	There is the capacity of the company to use information technologies involving machine learning and big data in order to improve information flow, develop the effective sharing of knowledge, and foster communication between members of the firm.					
		Our company's awareness of its competencies in innovation, especially with respect to key technologies such as machine learning and big data, and capability to eliminate obsolete internal knowledge is vital, thereby stimulating the search for alternative innovations and their adaptation.					
		There is the capacity to adapt technologies such as machine learning and big data, designed by others to the company's particular needs.					
		There is a degree to which the company prevents all employees voluntarily transmitting useful scientific and technological information shared by each other.					
		The company has the capacity to coordinate and integrate all phases of the R&D process and its interrelations with the functional tasks of engineering, production, and marketing.					
	Application	The organization's capacity to use and exploit new knowledge in the workplace to respond quickly to environment changes.					
		There is a degree of application of knowledge and experience acquired in the technological and business fields prioritized in the company's strategy that enables it to keep itself at the technological leading edge in the business.					
		The company has the capacity to put technological knowledge into products and process patents.					
		The company has the ability to respond to the requirements of demand or to competitive pressure, rather than innovating to gain competitiveness by broadening the portfolio of new products, capabilities, and technology ideas.					
Competitive Advantage	Differentiation Advantage	Compared to competing products, our products offer superior benefits to customers using machine learning and big data.					
		Our products are unique, and nobody but our company can offer them.					
		We take great efforts in building a strong brand name -nobody can easily copy that.					
		We successfully differentiate ourselves from others through effective advertising and promotion campaigns.					

	Cost Advantage	Our manufacturing costs are lower than our competitors due to machine learning and big data.					
		Our efficient internal operation system has decreased the cost of our products.					
		Our economy of scale enables us to achieve a cost advantage.					
		We have achieved a cost leadership position in the industry.					
	Institutional Advantage	Compared to our competitors, we have advantages In: Securing local resources such as land, electricity, and human resources; Obtaining external fund and financing; Gaining government support and approval; expediting project approval from relevant authorities.					

Appendix C: Copyright Permission

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ORIGINAL RESEARCH
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The Effect of Relational Embeddedness, Absorptive Capacity, and Learning Orientation on SMEs' Competitive Advantage

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Test Shown: Full

Test Format:
Responses for the 52 items ranged from 1 (strongly disagree) and 5 (Strongly agree) on a 5-point Likert Scale.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Permissions:

Appendix D: Survey Questions Analysis Key

This analysis is a representation key of the Wu et al.'s survey instrument. Each key represents part of the survey taken by participants. This key is developed for ease of computation within the statistical analysis found in the doctoral study.

		Key
Strategic Dexterity		
Strong Ties	Our company received support from our domestic partners in managerial resources.	SD1
	Our company received support from our domestic partners in emotional support.	SD2
	Our company received support from our domestic partners in time.	SD3
Trust	Because of doing business for so long, our company and partners understand each other well and quickly.	SD4
	In our contacts with domestic partners, we have never had the feeling of being misled.	SD5
	Both sides are expected not to make demands that can seriously damage the interests of the other.	SD6
	The strongest side is expected not to pursue its interest at all costs.	SD7
	Informal agreements have the same significance as formal contracts.	SD8
	Both sides know the weaknesses of the other and do not take advantage of them.	SD9
Shared System	The systems have been tailored to using the systems brought from domestic partners	SD10
	The domestic partners developed specific procedures for us to follow.	SD11
	The domestic partners have made efforts to instill its business philosophy in our managers.	SD12
Commitment to Learning	The sense around here is that employee learning is an investment, not an expense.	SD13
	The basic values of this organization include learning as key to improvement.	SD14
	Learning in my organization is seen as a key commodity necessary to guarantee organizational survival.	SD15
	Managers basically agree that our organization's ability to learn is the key to our competitive advantage.	SD16
Share Vision	All employees are committed to the goals of the organization.	SD17
	There is total agreement on our organizational vision across all levels, functions, and divisions.	SD18
	There is a commonality of purpose in my organization.	SD19
	Employees view themselves responsible for the direction of the organization.	SD20
	Employees view themselves as partners in charting the direction of the organization.	SD21

Open-mindedness	Managers basically agree that it is important to accept diverse viewpoints.	SD22
	We are not afraid to reflect critically on the shared assumptions we have made about our customers.	SD23
	Our organization pays much attention to original ideas.	SD24
	The culture in our organization emphasizes continuous innovation.	SD25
Absorptive Capacity		
Acquisition	Capacity to capture relevant, continuous, and up-to-date information and knowledge on current and potential competitors involving machine learning and big data.	AC1
	Degree of management orientation toward waiting to see what happens within machine learning and big data, instead of concern for and orientation toward their environment to monitor trends continuously and at a wide range and to discover new opportunities to be exploited proactively.	AC2
	Frequency and importance of cooperation with R&D organizations on machine learning and big data - universities, business schools, technological institutes, etc., as a member or sponsor to create knowledge and innovations.	AC3
	Effectiveness in establishing programs oriented toward the internal development of technological acquisitions of competences from R&D centers, suppliers or customers on machine learning and big data.	AC4
Assimilation	Capacity to assimilate new technologies and innovations such as machine learning and big data that are useful or have proven potential.	AC5
	Ability to use employee's level of knowledge, experience, and competencies in the assimilation of machine learning and big data, and interpretation of new knowledge.	AC6
	Degree to which company employees attend and present papers on machine learning and big data at scientific conferences and congresses are integrated as lecturers at universities or business schools or receive outside staff on research attachments.	AC7
	Attendance of training courses, trade fairs, and meetings on machine learning and big data.	AC8
	Ability to develop knowledge management programs, guaranteeing the firm's capacity for understanding and carefully analyzing knowledge and technology from other organizations.	AC9
Transformation	Capacity of the company to use information technologies involving machine learning and big data in order to improve information flow, develop the effective sharing of knowledge, and foster communication between members of the firm.	AC10
	Firm's awareness of its competencies in innovation, especially with respect to key technologies such as machine learning and big data, and capability to eliminate obsolete internal knowledge, thereby stimulating the search for alternative innovations and their adaptation.	AC11

	Capacity to adapt technologies such as machine learning and big data, designed by others to the firm's particular needs.	AC12
	Degree to which firm prevents all employees voluntarily transmitting useful scientific and technological information shared by each other.	AC13
	Capacity to coordinate and integrate all phases of the R&D process and its interrelations with the functional tasks of engineering, production, and marketing.	AC14
Application	The organization's capacity to use and exploit new knowledge in the workplace to respond quickly to environment changes.	AC15
	Degree of application of knowledge and experience acquired in the technological and business fields prioritized in the firm's strategy that enables it to keep itself at the technological leading edge in the business.	AC16
	Capacity to put technological knowledge into products and process patents.	AC17
	Ability to respond to the requirements of demand or to competitive pressure, rather than innovating to gain competitiveness by broadening the portfolio of new products, capabilities, and technology ideas.	AC18
Competitive Advantage		
Differentiation Advantage	Compared to competing products, our products offer superior benefits to customers using machine learning and big data.	CA1
	Our products are unique, and nobody but our company can offer them.	CA2
	We take great efforts in building a strong brand name -nobody can easily copy that.	CA3
	We successfully differentiate ourselves from others through effective advertising and promotion campaigns.	CA4
Cost Advantage	Our manufacturing costs are lower than our competitors due to machine learning and big data.	CA5
	Our efficient internal operation system has decreased the cost of our products.	CA6
	Our economy of scale enables us to achieve a cost advantage.	CA7
	We have achieved a cost leadership position in the industry.	CA8
Institutional Advantage	Compared to our competitors, we have advantages In: Securing local resources such as land, electricity, and human resources; Obtaining external fund and financing; Gaining government support and approval; expediting project approval from relevant authorities.	CA9