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Innovation-Driven Growth in Heavy Equipment Firms

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This is to certify that the doctoral study by

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Abstract

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Lack of innovation-driven revenue growth can have adverse effects on organizational outcomes. Company leaders who do not pursue innovation put their firm's survival at risk. Grounded in Christensen's theory of disruptive innovation and Rogers's diffusion of innovation theory, the purpose of this quantitative correlational study was to examine the relationship between company culture, company maturity, company revenue, and innovation-driven revenue growth rate in global heavy equipment manufacturing firms. Secondary data (N = 50) were collected from the *Yellow Table*, an annual listing of the top 50 global heavy equipment companies by revenue from 2002 to 2018. The results of the binary logistic regression were not significant, $\chi^2(8, N = 50) = 8.84$, $p = .356$. A key finding is that Japanese-culture companies are more likely to have high innovation-driven growth rates. The implications for positive social change include the opportunity for leaders to embrace new technologies and train and equip workforces to be ready to thrive in future environments, which could sustain and grow employment levels.

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Dedication

This work is dedicated to my beautiful wife, Wendy, and our two wonderful children, Josée and Alex. You inspire me every day to be a better husband, father, and person. Thank you for your patience, the countless sacrifices you made, the unconditional support you never failed to provide, and the constant reminders of all the blessings abundant in my life. With all my love, this is for you.

Acknowledgments

I would like to thank my committee chair, Dr. Matthew Knight, for your expertise, guidance, patience, and encouragement throughout this process. You were the reason I kept going through many difficult periods. I would also like to thank and acknowledge my committee members, Dr. Cheryl Lentz and Dr. Reginald Taylor, for their guidance and support, and also to all my peers and classmates who always inspired me to continue.

A special thank you to my immediate and extended family, whose support and encouragement made this possible. To my late parents, Leo and Rita Gallant, who instilled in me a lifelong desire to continue to learn and grow, my everlasting appreciation and wish you were here to celebrate this accomplishment with me.

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Section 1: Foundation of the Study

Enterprise leaders operate in a complex and continuously changing environment and need to successfully innovate to maintain industry relevance and growth for the enrichment of customers, employees, and stakeholders (Carnes, Chirico, Hitt, Huh, & Pisano, 2017; Hausman & Johnston, 2014). Business leaders recognize that innovation can be disruptive, expensive, and uncertain: simultaneously creating new industries, companies, and wealth while rendering existing business models obsolete and irrelevant (Christensen, 1997; Christensen, Dillon, Hall, & Duncan, 2016). The purpose of this study was to research innovation-driven revenue growth in the global heavy equipment industry.

Background of the Problem

Innovation, from a business perspective, is a combination of the invention, a novel concept or idea; and exploitation, the diffusion of the invention to derive economic benefit (Cohen & Caner, 2016; Salehi & Yaghtin, 2015). Innovation facilitates the creation and sharing of wealth and allows society to move toward sustainable footprints (Baranenko, Dudin, Lyasnikov, & Busygin, 2014; Colombo, Franzoni, & Veugelers, 2015). Within the business and investment community, leaders recognize innovation as a critical driver of economic and entrepreneurial growth (Carnes et al., 2017; Hausman & Johnston, 2014), and therefore innovation is an essential component of a leader’s growth strategies.

The launch of new products into markets is the driver of growth, not research and development (R&D) investments (Hausman & Johnston, 2014). The reality for most companies is that the development of innovative new products is fraught with financial, timing, and market risks, and is far from a predictable investment (Seifert, Tancrez, & Biçer, 2016). Many of the top innovating companies increase their R&D expenditures to maintain competitiveness, even in periods when profits continue to fall (Slater, Mohr, & Sengupta, 2014). Business leaders strive to use R&D investments wisely to deliver innovations to the market that drive productivity, revenue, and profit (Guisado-González, Vila-Alonso, & Guisado-Tato, 2016).

Problem Statement

Lack of innovation-driven revenue growth places the survivability of firms at risk (Forés & Camisón, 2016; Kostis, Kafka, & Petrakis, 2018). In a longitudinal study of over 5,000 U.S. manufacturing firms across a range of industries, innovative products accounted for 27% of total annual business unit sales (Arora, Cohen, & Walsh, 2016). The general business problem is that failure to increase innovation-driven revenue growth is detrimental to the sustainability of the firm. The specific business problem is that some leaders in the equipment industry do not know the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth.

Purpose Statement

The purpose of this quantitative correlational study was to examine the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth. The independent variables were company culture, company maturity, and total annual company revenue. The dependent variable was annual revenue growth driven by innovations. The population was multinational, heavy equipment manufacturing companies operating globally from 2002 through 2018. The implications for positive social change include the potential to assist heavy equipment company leaders to better leverage R&D investments and train the workforce for improvement of infrastructure in an efficient and environmentally sound manner (see Adams, Jeanrenaud, Bessant, Denyer, & Overy, 2016; Kuzemko, Lockwood, Mitchell, & Hoggett, 2016).

Nature of the Study

Researchers use a qualitative study design to determine the *what, how,* or *why* of a social phenomenon, whereas a quantitative study design is used to assess the existence or nonexistence of relationships among chosen variables (McCusker & Gunaydin, 2015). I selected quantitative methodology for the study, which included the mathematical examination of the relationships between variables to test one or more hypotheses (see Rovai, Baker, & Ponton, 2013). The examination of correlational relationships in hypothesis testing allows the generalization of significant statistical results to larger populations, whereas qualitative studies results are relevant only to the sampled participants and their experiences of the phenomenon (Punch, 2013; Rovai et al., 2013). Mixed-methods studies combine qualitative and quantitative approaches in a single study to explore the phenomenon based on a chosen paradigm (Shannon-Baker, 2016; Stockman, 2015). This study was not intended to explore the phenomenon of innovation-driven revenue or participants’ reactions or experiences. Therefore, qualitative and mixed-methods approaches were not suitable.

A correlational design is used by researchers to define the degree and patterns in the relationships, if any, between the variables (C. Y. Lee, Lee, & Gaur, 2017). Experimental or quasiexperimental designs require the possibility to manipulate the independent variables or study participants and observe the results (Rovai et al., 2013). Researchers use descriptive designs to define a particular phenomenon in great detail but cannot produce a rich statistical analysis of the relationships (Punch, 2013). Changes in innovation-driven revenue are only visible over multiyear periods. A correlational design including secondary data was chosen for the current study. I did not select an experimental, quasiexperimental, or descriptive design because there was a limited possibility to manipulate the independent variables, document participant experiences, or interview participants regarding past events.

Research Question

What is the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth?

Hypotheses

H_0: There is no likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth.

H_a: There is a likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth.

Theoretical Framework

For an innovation to be commercially successful, the novel idea or service the innovation contains must spread through the target population, and the potential buyers need to be aware of the benefits before making a favorable buying decision (Rogers, 2003). Rogers's 1962 theory of innovation diffusion presented a model for how the diffusion of innovation occurs over time and described the types of potential customers at each stage of development (Rogers, 2003).

Rogers's theory focused on individuals/agents and their buying behaviors and introduced personas such as early adopters, majority buyers, and laggards into the marketing lexicon (Ekdale, Singer, Tully, & Harmsen, 2015). In the fifth edition of the *Diffusion of Innovations*, Rogers (2003) expanded beyond individual agents and to the organizational characteristics of innovating firms, including culture, size, and maturity; and explained how organizations also fit within the diffusion model. When applying the diffusion model to a business-to-business situation, Rogers theorized that organizational culture parallels the agent personalities, and business networks replicate the agent's social networks in the diffusion process.

Christensen's (1997) theories on disruptive innovations provided the secondary theoretical framework for the current study and supplemented Rogers's theory of innovation on organizations. Christensen built on Schumpeter's creative destruction economic theory on innovation, but Christensen extended the discussion to two different innovation types termed incremental or disruptive. Further, Christensen stated that each type of innovation would have different effects on the industry landscape and offer opportunities for incumbent and emerging firms.

Operational Definitions

Diffusion of innovation: Diffusion of innovation is the process by which an innovation spreads throughout the population (Peres, Muller, & Mahajan, 2010; Rogers, 2003).

Innovation: Innovation is the commercialization of an invention to deliver a business benefit (Christensen, 1997; Salehi & Yaghtin, 2015; Snyder, Witell, Gustafsson, Fombelle, & Kristensson, 2016; Utterback, 1996).

Invention: The invention is the conception and development of an idea into a workable solution (Arora et al., 2016; Salehi & Yaghtin, 2015).

Radical innovation: Radical innovations, sometimes termed disruptive, discontinuous, or revolutionary, are innovations that have a transformative effect resulting in the emergence of new technology and a new business model (Christensen, 1997; Colombo et al., 2015; Saunders & Kilvington, 2016).

Semiradical innovations: Semiradical innovations involve substantial changes to either the business model or underlying technology, but not both (Saunders & Kilvington, 2016).

Sustaining/incremental innovation: The most common form of innovation, incremental or sustaining innovations are the small, continual changes in process or product (Christensen, 1997; Saunders & Kilvington, 2016).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are statements believed to be true and self-evident (Dean, 2014). The most significant assumption for the current study was that there were two driving demand factors for revenue growth in any industry (a) demand through innovation and (b) demand created by demographic and economic changes (see Ang & Madsen, 2015; Leimbach, Kriegler, Roming, & Schwanitz, 2017). The current study focused on the demand created through successful innovations that generate revenue from new markets, applications, and utility. The effect of changes in demographics is creating equal opportunities among companies in the market and will equalize over time, while revenue growth may differ based on competitiveness influenced by innovation changes (Christensen, 1997; Fedderke & Liu, 2017). This assumption holds under a broad definition of innovation as used in the current study, where innovation is any new process, product, technology, or market approach that has commercial benefit.

An additional assumption regarding the diffusion of innovations was that existing processes and dominant technologies drive incremental innovations and will diffuse very quickly throughout the industry (see Carnes et al., 2017). As a result of the rapid diffusion, incremental innovations do not deliver sustainable mid- and long-term competitive advantage and market share gains (J. Lee & Berente, 2013; Slater et al., 2014). The mechanism of diffusion for incremental innovations is similar between geographies, products, and industries, although the speed of the diffusion may vary (Christensen, 1997; Rogers, 2003).

Data for this study were obtained from secondary sources, primarily the *KHL Yellow Tables* from 2002 to 2018. The *Yellow Table* is an annual compilation of the revenue of the top 50 global heavy equipment companies, reported by *International Construction* magazine editorial staff (Sleight, 2013). For the current study, I assumed the revenue data in the secondary sources were accurate and valid.

Limitations

Limitations of a study include theoretical or methodological conditions in the chosen research approach over which the researcher has limited control, but may weaken the study without compromising the validity (Busse, Kach, & Wagner, 2017; Kowalkowski, Windahl, Kindström, & Gebauer, 2015). The current study included two significant limitations. KHL publishing group compiles and publishes the *Yellow Table* in the April issue of *International Construction* magazine (Sleight, 2013). Secondary data collected for other primary research purposes may not align with the delimitations of a study, the original collection methods may be unknown to the researcher, and follow-up inquiries regarding the data set may not be possible (Johnston, 2017). I made sure the secondary data in the study were from a reputable industry publication, and where possible, I verified the data with other public data sources. The secondary data set chosen from the *Yellow Table* included companies' revenue by year and was aligned with the current study's population, time frame, and geography.

I separated the innovation-driven revenue from the total revenue by factoring out the demographic and market effects, which affect all companies in the industry. I recognized a limitation in that all companies in the industry benefit from some level of incremental innovation, which may have resulted in understating innovation-driven growth revenues in the study because incremental innovations were not included (see Christensen, 1997; Fedderke & Liu, 2017).

Delimitations

Delimitations are the boundaries of the study as defined by the researcher (Busse et al., 2017; Dean, 2014). The current study focused on the heavy equipment industry; results may vary in other sectors and products (see Tidd & Thuriaux-Alemán, 2016). Data were collected from 2002 to 2018 for the top 50 companies in the global heavy equipment industry. The correlations between variables in this study were specific to companies within this industry, and results are generalizable only to enterprises that have similar innovation diffusion cycles and R&D investments (see Tavassoli, 2015).

In this study, the focus was on the incremental and semiradical innovations that change the relative competitiveness of companies and the effect on the annual revenues (see Christensen, 1997). Incremental and semiradical innovations work within the same technology or business model and do not result in new industries or applications (Christensen, 1997; Saunders & Kilvington, 2016). Disruptive innovations, in contrast, involve fundamental changes in the technology and business model and may drive new applications and new industries (Christensen, 1997; Saunders & Kilvington, 2016). Disruptive innovations were not the focus of this study.

Significance of the Study

Companies invest significant capital in developing innovation through R&D and process improvement programs, but leaders have no reliable benchmark to understand whether the company maintains competitiveness toward the best-performing companies. In the absence of industry benchmarks on innovation, including the performance of high performing innovators, leaders make decisions on funding and possible returns in a vacuum (Ikeda & Marshall, 2016). Leaders can use knowledge of current innovation variable relationships to understand innovation diffusion already present in the industry and develop specialized organizational structures to drive growth through innovations (Ikeda & Marshall, 2016).

The current study may also be significant for the understanding of innovation as a productivity and growth driver within societies to allow the development of sustainable industries and protect limited nonrenewable resources based on knowledge and organizational learning (see Chiva, Ghauri, & Alegre, 2014; Lubberink, Blok, Van Ophem, & Omta, 2017). Workers in industrial manufacturing industries, especially older workers with secondary education, can make the transition to the high-tech knowledge economies and drive innovative growth if provided the right environment and training (Ang & Madsen, 2015). The implication for positive social change from the study was that leaders of traditional heavy manufacturing industries might better understand how to train and motivate employees to capitalize on innovations driven by the new paradigm of organizational knowledge, innovation, and internationalization.

A Review of the Professional and Academic Literature

In the competitive business environment of the 21st century, innovation in all forms is a crucial driver for sustainable industrial growth for companies, industries, and nations (Lubberink et al., 2017). Many of the most successful enterprises in the world, as well as entire industries, are the product of successful innovation management (Christensen, McDonald, Altman, & Palmer, 2018). Examples of companies built on innovation appear in all industries and include well-known iconic brands such as Apple, Amazon, Boeing, Google, Intel, Samsung, Toyota, and Walmart (Alhaddi, 2016; Choi, 2019; Christensen et al., 2016; Christensen et al., 2018; Shenhar, Holzmann, Melamed, & Zhao, 2016).

Business leaders use innovation to gain a competitive advantage; however, the concept of innovation did not emerge in the business lexicon until after 1910 when Schumpeter introduced the concept of innovation in economic analysis using what he termed the creative destruction model (Utterback, 1996). Based on the early economic theories of the 1920s and 1930s, innovation research has been prolific in numerous fields, including engineering and technology, public policy, medicine, social research, business management, systems dynamics, and most recently the information technology disciplines (Christensen et al., 2016). The scholarly material available on innovation is diverse, robust, and comprehensive, with thousands of articles available in academic libraries or traditional press sources on the general topic of innovation. Innovation management is a broad and complex subject, intertwined with many intellectual disciplines and social structures. Independent of the extensive database of scholarly articles in existence, the intellectual understanding of the innovation phenomenon is not complete, and gaps exist in the literature, especially when defining the cyclical and sometimes chaotic nature of innovation and the organizational learning process (Chiva et al., 2014; Frow, Nenonen, Payne, & Storbacka, 2015; Mastrogiorgio & Gilsing, 2016).

Two general methodologies of literature reviews are available to scholars. A traditional literature review is used to provide a broad synthesis of the existing literature on a particular topic and identify research trends, including significant shifts (Campanelli & Parreiras, 2015). Systematic literature reviews differ in that the goal is to provide an in-depth consideration of the literature on a narrow topic, as denoted in the research questions (Campanelli & Parreiras, 2015). Systematic literature reviews are narrative, descriptive, or scoping (Paré, Trudel, Jaana, & Kitsiou, 2015). Given the voluminous literature available on the general topic of innovation, a systematic literature review was the best choice to maintain focus on the research question while ensuring coverage of the relevant literature.

The expectations of quantitative research are (a) the representation is neutral, the study is explicit, (b) the research builds on prior relevant empirical studies, and (c) the research is reproducible (Paré et al., 2015; Peters et al., 2015). The best choice of systematic literature review typology for the current study was a systematic scoping review focused on the research question and the theoretical framework theories (see Paré et al., 2015; Peters et al., 2015). The literature review was primarily for a general academic audience, including the study review committee.

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Except for the purchased book sources, all references cited in the study were accessed online using Walden University library databases, including ProQuest, ScienceDirect, Emerald Insight, ABI/INFORM, and Business Source Complete. I employed Google Scholar as the first search engine for locating articles, using the initial keyword combinations of *innovation*, *forecasting*, *forecast models*, *life cycle curves*, *product life curves*, *complex systems*, *incremental*, *sustaining*, *disruption*, and *radical*. Mapping of the writings of prominent scholars on the topic clarified the linkages between theories, dissenting views, and development history. An expectation for graduate research in business is that current peer-reviewed sources constitute many of the cited sources. The study contained 124 references, of which 106 (85.5%) were peer reviewed and published after 2015.

Innovation

As early as 1912, Schumpeter introduced innovation as a core component of growth and competitiveness in a process that he called creative destruction (Utterback, 1996). Schumpeter theorized that innovation created new opportunities that would, over time, destroy existing companies and products while simultaneously creating new companies and industries (Woodside, Bernal, & Coduras, 2016). Innovation facilitates the creation and sharing of wealth throughout the world and allows society to move toward sustainable footprints (Baranenko et al., 2014; Colombo et al., 2015). Early and continual innovation is a critical factor in companies surviving financial shocks and emerging in leading positions in the postcrisis years (Hausman & Johnston, 2014). Without innovation in products and processes, markets would stagnate with growth limited to the demand changes driven by population demographics only (Fedderke & Liu, 2017). For this reason, businesses and governments have a societal and fiduciary responsibility to manage innovation, minimize damages, and maximize benefits over the long-term to maintain the growth of their economies and companies.

Types of innovation. Much of the scholarly research into innovation has focused on radical or disruptive innovations, which may produce new industries, business models, product classes, or product replacements (Colombo et al., 2015; Nagy, Schuessler, & Dubinsky, 2016). However, most innovations in an industry are not disruptive and do not create new business models. Researchers called nondisruptive innovations sustaining or incremental innovations, which are the output of most of the development activity in product development or engineering departments (Christensen, 1997; J. Lee & Berente, 2013). Small, incremental improvements are rarely proprietary or patentable and are quickly adopted by the competitors and suppliers (J. Lee & Berente, 2013). Incremental innovations do not dramatically change the industry because most concerned companies benefit equally from the innovation over the short term. For this reason, no sustainable competitive advantage or new business models result from incremental innovations (Slater et al., 2014).

Occasionally, companies will develop and bring to market innovations that provide a significant competitive advantage without creating a new industry-wide business model. These innovations are called semiradical innovations (Suder & Kahraman, 2015). The intellectual properties of semiradical technological innovations are frequently protected by patents in favor of the developing companies or inventors, and may eventually become the dominant technology or be supplanted by further innovation in the future.

Christensen's Theory of Disruptive Innovation

Christensen's (1997) *The Innovator's Dilemma* was the first significant scholarly work that addressed innovation as both a process and a strategy. Christensen concentrated on radical, disruptive innovations, which fundamentally changed the markets, products, or applications and created new and unique business models. Christensen theorized that incumbent, dominant companies with organizations designed to meet current demands were often unable or unwilling to change the company inertia and to focus on new first-mover advantages, leaving an opportunity for entrepreneurial companies to fill the need (Christensen, 1997; Colombo et al., 2015). Two preconditions exist for market disruption to occur (a) the innovation has to be attractive to a currently underserved customer base, and (b) there have to be incentives for customers and companies to enter into the newly created market space (Christensen, 1997). Christensen termed the failure of seemingly productive and well-managed incumbent companies to react to disruptive innovation as the innovator's dilemma (Christensen, 1997; Forés & Camisón, 2016).

Christensen’s (1997) theory detailed why incumbent companies may be at a disadvantage concerning disruptive innovations when radical technology creates new market applications or significantly changes the existing processes and routines. However, there have been many instances in which incumbent companies have developed and exploited radical innovations (Eggers & Kaul, 2018). Leaders in companies with high levels of technical competence and established processes may choose to continue to exploit the technological competence within the firm and continue to innovate in the dominant technology, substantially extending the technology lifecycle (Eggers & Kaul, 2018). Alternatively, incumbent company leaders may use relational entry methods to partner or joint venture with other firms that have the desired technical competencies, including firms in the existing supply chain (Shenhar et al., 2016). As a third alternative, companies may choose a hierarchical approach and set up a new division or acquire a company with competence in the latest technology (Eggers & Kaul, 2018).

One of the significant criticisms of Christensen’s disruptive theories was that the results are only observable on an ex-ante basis, and therefore the theory may have limited predictive capability (Weeks, 2015). A series of trials using graduate business students was conducted to test the predictability of the theory, where the students predicted success or failures of innovations without knowing the outcomes (Christensen et al., 2018). Students using the theory had significantly more accurate predictions and demonstrated that the theory does have predictive capabilities, albeit with small sample sizes.

Innovation Diffusion

The invention is the first stage of the invention, innovation, and diffusion process in which an inventor transforms a novel idea into a new product or process. Unless the economic benefit is available through an appropriate business model to provide financial rewards to the stakeholders, the invention has little relevance in business (Arora et al., 2016; Snyder et al., 2016). Peres et al. (2010) identified two types of innovation diffusion (a) diffusion within markets and (b) diffusion across markets and brands. Social networks, network externalities, and technology generations influence diffusion rates within markets (Peres et al., 2010). For diffusion across markets or brands, the effect of national culture and a leader’s learned behavior becomes significant (Chiva et al., 2014; Peres et al., 2010). Cross-market diffusion has a lead-lag effect in which markets, customers, and companies may wait and evaluate the suitability of the innovation before committing to it, thereby lowering risk and development expenditures (Peres et al., 2010).

Systems Theories

A novel idea or technology is not sufficient for successful business innovation (Åstebro & Serrano, 2015). The diffusion of innovation through the target population requires a social network, proper communication channels, and adequate time for the adoption to occur (Rogers, 2003). Nan et al. (2014) noted that leaders use the innovation system to describe the combination and social interactions among these elements and use tools and frameworks from systems theories to view all the interactions. Early system theories and researchers on innovation tended to view the interactions between the elements in a linear, causal manner, occurring only once in each innovation lifecycle

(Chiva et al., 2014; Rogers, 2003). The development of complexity theory in the mid-1990s allowed scholars to view innovation diffusion systems as complex systems, often operating on the edge of chaos and continually adapting and transcending the original conditions (Chiva et al., 2014).

Rogers's Theory of Diffusion of Innovation

The primary adoption or diffusion curve for innovation has a characteristic shape known as an S-curve. The innovation has a slow approval by early adopters, followed by a steep rise in demand once the user becomes aware of the benefits (Chang, Kibel, Brooks, & Chung, 2015; Rogers, 2003). The steep rise precedes a mature phase, in which revenue is stable and predictable each year, and eventually a decline as a future innovative product replaces the current version (Rogers, 2003). The innovation adoption curve, first proposed by Frank Bass in 1959, is a representation of the Gaussian mathematics of the normal or bell curve population distribution (Peres et al., 2010).

The general formula for the normal distribution of the means of a population is f(x) = $e^{[-(x-\mu)^2/(2\sigma^2\ )]/[\sigma(2\pi)^{1/2}]}$, where x is the population mean, μ is the sample mean, and σ is the sample standard deviation. For simplicity, statisticians rewrite the normal distribution equation as $f(x)$ = $ae^{[-(x-\mu)^2/2\sigma^2]}$, where $a = 1/[\sigma(2\pi)^{1/2}]$ mathematically defines the maximum height of the curve. Figure 1 shows the standard normal curve and the frequency distribution at multiples of the standard deviation.

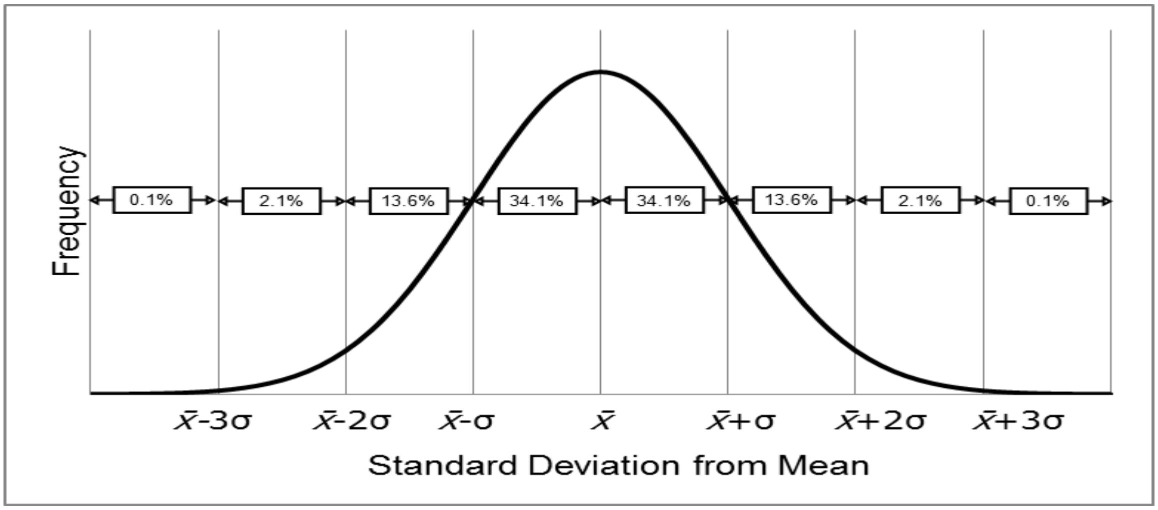

Figure 1. Frequency distribution curve around the population mean.

From this distribution, a person can predict the proportion of the population expected to adopt the innovation at given time intervals. According to Rogers's (2003) theory of innovation diffusion, five different adaption types exist in any market as defined by the normal curve. Individual agents accepting the innovation at time intervals more than two standard deviations before the mean are called *innovators*, between one and two standard deviations from the mean are *early adopters*, one standard deviation before the mean are *early majority* buyers, and from zero to one deviation above the mean are the *late majority buyers* (Rogers, 2003). All remaining buyers above the mean by one or more standard deviations are known as laggards and constitute 15.7% of the general population based on the normal bell curve (Peres et al., 2010; Rogers, 2003).

The cumulative sales of the market demand for the innovation produce an S-type growth curve, or a Bass diffusion curve, as shown in Figure 2. If a person represents the total population from 0 to 1, they can simplify the Bass diffusion curve to symmetrical unit distribution: $f(x)=1/[1+e^{-x}]$. The symmetrical unit model is an essential derivation in statistics, and the logit or linearizing log function of the model is the basis for logistic regression (Hosmer, Lemeshow, & Sturdivant, 2013). The differential of the unit curve formula mathematically describes the slope of the curve at any point, equal to the rate of growth of the function at that point (West, 2015): $f'(x)=f(x)[1-f(x)]$.

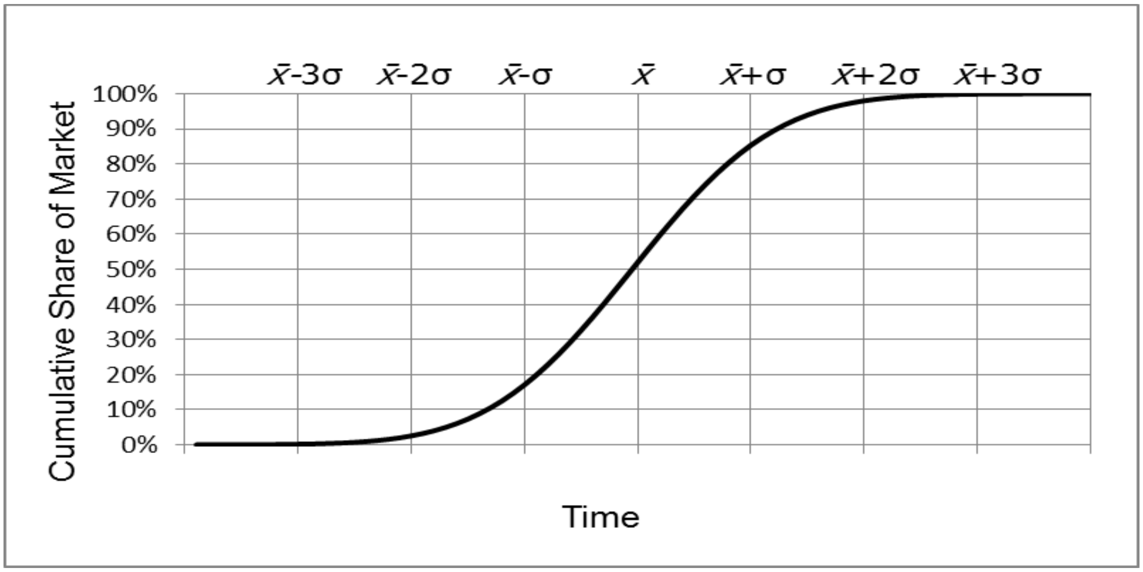

Figure 2. S-curve based on symmetrical normal frequency distribution.

The theoretical curves models represent the contributions of individual agents and display the rate at which a singular innovation may diffuse into the market throughout the life cycle of the products (Massiani & Gohs, 2015; Wang, Pei, & Wang, 2017). In the general Bass model, factors show the effects of seasonality and network externalities on the diffusion of innovations and corresponding revenue changes (Wang et al., 2017). On a macroscale, diffusion curves can be used to model the summation of the resultant sales over time from all the innovations from a particular company or industry (Taylor & Taylor, 2012).

Utterback (1996) described three stages of the life cycle slightly differently than Rogers (2003). Utterback described the life cycle beginning with the fluid stage, followed by a transitional stage, and terminating at the specific stage (Utterback, 1996). In the initial fluid phase, the product undergoes significant technical revisions; only the early adopters are interested in the products during the fluid phase (J. Lee & Berente, 2013; Taylor & Taylor, 2012). Rapid increases in the market uptake characterize the transitional period, the creation of production capacity to meet the demand increase, and relatively few primary product or technological innovations (J. Lee & Berente, 2013; Taylor & Taylor, 2012). Finally, companies will enter into a specific phase, where only minor incremental innovations are made to product and process to maintain the products until the following new disruptive innovation occurs (Taylor & Taylor, 2012). The types of innovations change during the life cycle; explorative product innovations precede exploitative process innovations, followed by market position innovations, and finally, paradigm explorative product innovations, which usher in a new technological disruption to renew the cycle (Carnes et al., 2017; Gao et al., 2017).

S-curves are a theoretical construct; actual curves are not as smooth and predictable as the theory predicts due to the influence of various market and diffusion variables and technical generations (Peres et al., 2010; Taylor & Taylor, 2012). In many cases, companies will experience a rapid rise in revenue, often as much as 30%, early in the curve as the early adopters embrace innovation (H. Lee & Markham, 2016; Peres et al., 2010). Shortly afterward, as companies compete to wrest production resources to fulfill the takeoff curve demand, there may be a drop, called the saddle or chasm (Peres et al., 2010). The saddle represents a demand reduction, as early majority customers wait to evaluate new technology, or until lean and efficient production operations are in place

(Peres et al., 2010). At the end of the saddle, once proving an innovation and production rates match demand, the rapid growth in the innovation will resume.

The life cycle approach is an analogy to human aging and biological life cycles. Similar to an organic life growth, the business or product lifecycle has an uncertain beginning phase, a rapid development period, before settling to a long mature phase, and eventual into decline (Levie & Lichtenstein, 2010). The life cycle model remains attractive to scholars and business professionals because it defines core components (life stages), sets forth a logic explaining the relationship between the phases, and applies to products and companies everywhere (Levie & Lichtenstein, 2010). Further investigation revealed that the biological life cycle analogy does not necessarily hold as enterprises and products do not adhere to a linear or convex progression, and the development of products and businesses does not occur by a set of unalterable, subsequent stages (Levie & Lichtenstein, 2010). Since 2010, scholars replace the notion of a biological life cycle by complex, dynamic states models (Chiva et al., 2014; Levie & Lichtenstein, 2010; Tavassoli, 2015).

The standard linear life cycle curves represent models for product life cycle (PLC), technology life cycles (TLC), company or organization life cycle (OLC), and industry life cycles (ILC) (J. Lee & Berente, 2013; Taylor & Taylor, 2012; Utterback, 1996). Research on product life cycles has been the topic of over 95% of the 4,545 identified lifecycle articles published from 1991 to 2011, and in only 2% of the published articles did the authors focus on the technical or business life cycles (Taylor & Taylor, 2012). The lack of scholarly articles on ILC or OLC would suggest an existing gap in understanding and research in the literature.

Life cycle curves are an accumulation of the individual diffusion curves over time (Rogers, 2003; Tavassoli, 2015). For example, a product lifecycle curve will include all the innovations, product generations, and improvements done to the product over time, each with a unique diffusion curve. In the same manner, the company or organizational life cycle curves are an accumulation of the individual product S-curves for a particular company, and an industry curve is the consolidation of the many industry participant firms (Rogers, 2003; Taylor & Taylor, 2012).

The cyclical nature of the life cycle models suggests that the timing of changes is predictable. The drivers of the schedule of the product cycle can be fad-driven, technology-driven, or regulatory and investment constrained, such as the pharmaceutical industry (Ang & Madsen, 2015). For any industry, the history of product innovations as well as the entry and exit of participating companies will give a good indication of the cycle timing and phase (Seifert et al., 2016). Although the technologies are far more sophisticated at each successive cycle, research suggests that product lifecycle periods decrease over time, especially in high tech industries (H. Lee & Markham, 2016). Increases in the rate of technological development, the rate of innovation diffusion, and the willingness of companies to adopt and promote these innovations may compress the cycle period (Rogers, 2003).

The cyclic nature of innovation diffusion is also evident over extended economic periods. Kondratiev economic waves (K-waves), have recurring periods of approximately

40 to 60 years, with booming economies at the peak of each cycle, and low economic periods in the troughs (Coccia, 2017b; Grinin, Grinin, & Korotayev, 2017). K-waves show the total economic resultant from the long-term coevolution of science, technology, economics, politics, and culture (Coccia, 2017b). Each new K-wave corresponds to an overarching technology shift, driving many of the macroeconomic changes, which result in disruptive or radical innovative shifts (Coccia, 2017b; Grinin et al., 2017; Linstone, 2011; Utterback, 1996).

Under the K-wave model, the *boom* corresponds to the late phases of the previous technological paradigm, where the rapid displacement of the technical innovation occurs, often in chaotic and unpredictable manners by newly emerging companies (Christensen, 1997; Utterback, 1996). The knowledge of the new technology quickly consolidates throughout the industry, and commercialization and diffusion of the new products drive rapid economic growth (Linstone, 2011). During this upswing, the old technologies may continue to be sold by incumbent companies, and improved by small incremental innovations, provided full displacement does not occur (Linstone, 2011). The subsequent downswing is the creative destruction phase, where new clusters of innovations and new technical paradigms emerge, which may lead to new companies and possibly entire industries once commercialized and diffused in the next upswing cycle (Christensen, 1997; Linstone, 2011). Figure 3 details the six previous K-wave cycles and the associated overarching technologies.

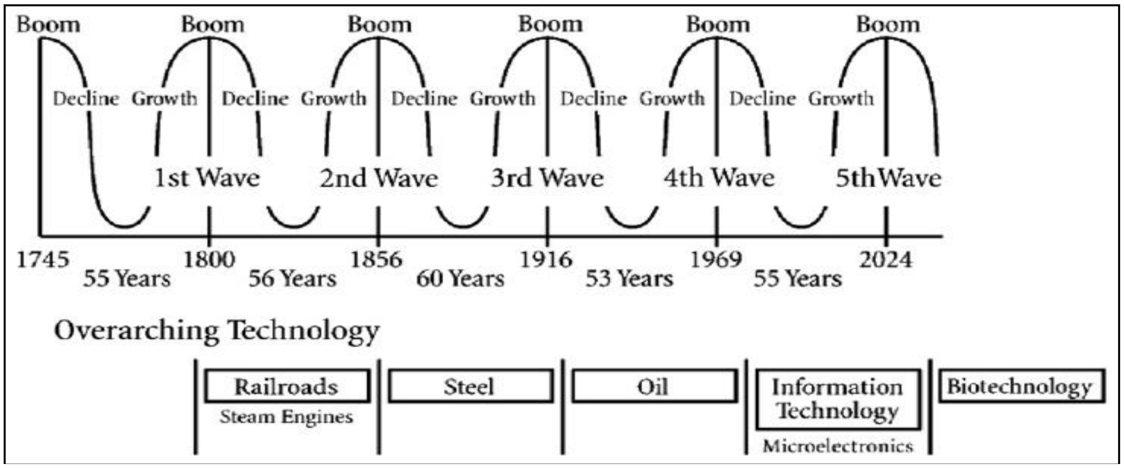

Figure 3. Six K-wave cycles and overarching technologies.
From "Three eras of technology foresight" by H. A. Linstone. Technovation, 31, p. 70. Copyright 2010 by Elsevier B.V. Reprinted with permission (see Appendix A).

Support exists in the literature for the correlation between K-waves, economic cycles, and business results, although the debate regarding causality continues (Coccia, 2017b, 2018; Focacci, 2017; Grinin et al., 2017). Economists identified a minimum of 20 past K-waves, and scholars have applied technology advancements and innovations to the last five K-wave cycles (Coccia, 2017b, 2018; Linstone, 2011). The current K-wave cycle around information technologies wave will peak around 2024, with a new technological shift toward nanotechnology and biotechnologies (Linstone, 2011).

Business leaders who can adapt to both the macro innovation and economic trends, as well as the short-term diffusion from product, technology, and industry life cycles, will have an advantage in predicting and managing the future directions for incremental and semiradical innovations. Matching available R&D investments with the proper type of innovation, at the right point in the economic cycle, will help leaders to maximize the probability of the success of the implementation of the innovation (Rogers, 2003). The study of the past cycles alone will not identify future radical innovations; therefore, leaders have to remain vigilant for developing technology breakthroughs.

Linear models and dominant design. In the classic life cycle model, markets continue to evolve until a dominant design emerges, supported by infrastructure and technology developments within leading incumbent companies (Christensen, 1997). After the establishment of the dominant design, the market will grow only through demographic demand growth and incremental innovations until a subsequent disruptive innovation emerges, and a new dominant design is established (Taylor & Taylor, 2012; Utterback, 1996). The companies benefiting from the new dominant design may not be the incumbent companies (Christensen, 1997; Utterback, 1996).

Christensen theorized that incumbent firms that had the dominant design would have difficulty in adapting to new technologies, a phenomenon he termed as *Innovator's Dilemma* (Carnes et al., 2017; Christensen, 1997). Christensen hypothesized that incumbent firms would not be able to respond to new technologies, primarily because of the substantial investment in technical competence, management, and process structures based on the existing dominant technology (Christensen, 1997; Christensen et al., 2018). For this reason, the new opportunities would be realized by emergent firms, often in different applications, and not recognized as an immediate threat to the incumbent's current business (Christensen, 1997). Although Christensen's (1997) disruptive innovation theory elegantly explained the cases highlighted in his book, the theory could not explain why other disruptive innovations did not follow similar patterns and displace the incumbent technology leaders. King and Baatartogtokh (2015) argued that incumbent firms could survive disruptive innovations if management were successful in reacting to the changes in the business model, and further, specific disruptive innovations could be complementary and coexist with existing business models for extended periods. If a dominant design and standards emerged in the industry around the current technology, then incumbents might survive and thrive by innovating toward process extending the lifecycle (Brem, Nylund, & Schuster, 2016). The existence of a dominant design does not have a significant negative relationship with disruptive innovations (Brem et al., 2016).

Complex systems and dynamic states. Differing viewpoints of the market cycle also give insight into the innovator's dilemma paradox. The neoclassic view of economic systems postulated that systems would continually seek equilibrium and that the final state could be defined through a set of linear variable assumptions if the initial conditions were known (Pirgmaier, 2017). In contrast to the linear, Marshallian view, the creative destruction viewpoint theorized continual reinvention and innovation in a nonlinear fashion and suggested the innovation system is nonlinear, adaptive, and emergent in nature (Rotolo, Hicks, & Martin, 2015). Systems that have characteristics of adaptation, emergence, and are self-organizing are often referred to as complex systems and are characteristic of many other social constructs (Katz, 2016; Rotolo et al., 2015).

Viewing the traditional S life cycle curve within the design of a complex system, the stages of the S-curve will no longer be sharply differentiated and restricted to linear, sequential movement through time (Levie & Lichtenstein, 2010). Scholars refer to the model resulting from the application of the S-curve within a complex system as a dynamic states model and can display any of the four phase states of complex systems (a) stable, (b) stably oscillating, (c) chaotic with predictable boundaries, and (d) unstable (Chiva et al., 2014; Levie & Lichtenstein, 2010; Linstone, 2011). Innovations occurring in the early phases of the product lifecycle curve may overlap other phases of the industry's life cycle curves (J. Lee & Berente, 2013; Linstone, 2011). New entrants will tend to adopt the latest technologies even before the benefits fully emerge. In contrast, leaders of incumbent companies invested in the previous dominant technology may find it hard to adapt (Christensen, 1997). The final equilibrium state of the model depends on the agents within the system, maximizing their utility, and by the actions of competitors through the imposition of system boundaries (Audretsch, Coad, & Segarra, 2014).

Nan et al. (2014) applied the principles of complex adaptive systems theory to innovation diffusion to view diffusion in the context of three constructs of agents, interactions, and the environment. Unlike linear causality models where the outcome is predictable based on the initial conditions and subsequent actions, a complex system model's outcome cannot be predicted in advance from the initial parameters (Chiva et al., 2014). Complex systems are adaptive, with the agents making decisions through constant interaction with each other and with the environment, including competitive threats (Nan et al., 2014). Successful agents of innovation diffusion have an awareness of the innovation, have the motivation, and can develop the innovation (Nan et al., 2014). Interactions between the agents and external company personnel provide the social framework for the dissemination of the technical knowledge and, if useful, promote acceptance of the innovation within the adoptors in the population (Nan et al., 2014; Rogers, 2003).

In support of Christensen’s theory, complex adaptive systems theorists suggest that if innovation is continuous, the agents in incumbent companies are likely to have the awareness, motivation, and capability to capture the benefits of the innovation (Christensen, 1997; Nan et al., 2014). If the innovation is discontinuous, however, agents invested in the existing technology may be reluctant to change, whereas agents in emerging companies may have greater awareness, motivation, and capability, as well as the social network to capitalize on the opportunity (Christensen, 1997; Nan et al., 2014).

Although K-waves or the long waves of the economic theory seem to be linear constructs, Coccia (2018) argued that the peaks and troughs of each cycle also represent unstable social periods, characterized by the presence of significant wars. The inventions that would fuel the next economic cycle and dominant technology emerged during these volatile periods, with unpredictable outcomes, and subsequently commercialized during the more linear upswing and downswing periods (Coccia, 2017b, 2018). Inventions that create new dominant technologies are disruptive innovations within Christensen’s disruptive innovation theory and Schumpeter’s creative destruction frameworks (Christensen, 1997; Utterback, 1996). A better understanding of the dynamics of the life cycles under all these viewpoints by business leaders will help them forecast when significant inventions and emerging technologies are most likely to occur, and when the diffusion of the inventions may be most suitable.

Business Models

Innovation is not a guarantee of commercial success. Innovations, regardless of their novelty or usefulness, are only successful in a capitalistic market when commercialized for the benefit of firms, industries, and society (Hausman & Johnston, 2014). A logical business model can help companies capture the value of the innovation, translate the value to products or services, and deliver these offerings to the right customers (Teece & Linden, 2017). Conversely, without a well-planned business model for innovation, companies may fail either to provide the innovation or to derive any commercial value from the customer transactions (Euchner, 2016; Teece & Linden, 2017). Leaders use a good business model as an operational blueprint for successful innovation by managing internal knowledge and skills, by continually exploring for new knowledge from outside sources, by cooperating on industrialization and commercialization of innovations, and maintaining an entrepreneurial lens to spot emerging opportunities (Carayannis, Sindakis, & Walter, 2015).

Teece and Linden (2017) suggested three business model approaches that companies can pursue to develop innovative product offerings. In a fully integrated business model, companies control the full value chain for innovation, including the design, the supply of many of the components, and the distribution of the products to end-user customers. A fully integrated model demands that the company has a robust development and distribution capability (Guisado-González et al., 2016; Teece & Linden, 2017). In contrast, leaders may opt to pursue a licensing strategy, outsourcing many of the business functions to third-party firms. In these cases, care must be exercised to ensure the company retains sufficient ownership of the intellectual property to derive satisfactory and unique customer value (Teece & Linden, 2017). Most innovating firms today practice a hybrid model, by which the company will internalize the innovation to develop the technology but outsource many of the nonsensitive functions to third-party companies (Carayannis et al., 2015; Forés & Camisón, 2016; Teece & Linden, 2017).

The measure of the viability of business models is the measurable financial benefits to the firm and stakeholders, meaning the advantages of the innovation must be successfully commercialized (Curado, Muñoz-Pascual, & Galende, 2018; Snyder et al., 2016). The knowledge-based value is the technical and production capabilities the firm derives from the innovation, but the firm must also have the resource-based value (RBV) sufficient to exploit the innovation in the marketplace (Curado et al., 2018; Tavassoli, 2015). Radical innovation diffusion into a market relies on the knowledge and technological capabilities of the employees, with direct interaction with the early adopter customers who are attracted to the innovation (Rogers, 2003). Radical innovations include a higher probability of occurrence if no dominant design exists (Brem et al., 2016). Given the high risk and failure rate of radical innovations, Ikeda and Marshall (2016) found that firms that had transparent measures of innovation spending and tracked ROI have a higher probability of securing funding and avoiding the volatility of annual or quarterly budgeting pressures.

Most industries have dominant designs or establish standards that lessen the probability of radical, disruptive innovation, and thereby provide stability and predictability to the industry and incumbent companies (Brem et al., 2016). Innovation management in these situations consists primarily of the small process and product improvements and is marketed to the early majority, late majority and laggard customers (Brem et al., 2016; Rogers, 2003). The dynamics of dominant design continue to change with the average life of a dominant design shrinking to as little as 1 year from the current average of 6 years if viewed across all industries (Brem et al., 2016).

The literature on innovation provides clear evidence that company variables, both internal and external, have an influence on innovation, and those diverse industries may adopt and diffuse innovations differently (Audretsch et al., 2014; Coad, Segarra, & Teruel, 2016; Rogers, 2003). As well as the firm and industry factors, other researchers have added external linkages, including open innovation, and environmental conditions as relevant mitigating factors on innovation (Nan et al., 2014). Innovation occurs across cultural boundaries; however, the effect of individual cultural behaviors on innovation is still unclear (Woodside et al., 2016). In general, individualism in culture has a high correlation to innovation; however, certain collectivist traits, such as the free flow of information and a high degree of organizational learning, can be positively correlated as well (Beyene, Sheng, & Wei, 2016). The advantages of local expertise clusters, common in individualistic settings, is being offset by the emergence of robust open innovation networks between organizations and sharing of information among collectivist and individualist countries and cultures (Ikeda & Marshall, 2016; Slater et al., 2014). Culture and political orientation also affect companies' innovation strategies (Abdi & Senin, 2015; Beyene et al., 2016). Company and national cultures that are active in advocacy will tend to favor innovation strategies whereas hierarchical orientation will favor imitation and follower strategies (Woodside et al., 2016). Business leaders who understand and can manage the interaction of their business models, the available funding, technology learnings, and the diffusion of innovative products within the cultures of their companies will have a higher probability of successful innovations.

Enterprise maturity and size. The maturity of the enterprise and the relative size in comparison to other industry players are factors toward innovation effectiveness in the different innovation types (Christensen, 1997; Guisado-González et al., 2016). The number of years a company has been active in the industry, the company age, is a representation of the maturity of the company in the industry (Forés & Camisón, 2016; Tavassoli, 2015). Larger and mature companies favor existing process and incremental innovation, but also have resources and capabilities for semiradical innovations that smaller businesses cannot afford (Guisado-González et al., 2016; Nicolau & Santa-María, 2015). By contrast, small emerging companies tend to exhibit high levels of organization innovation (OI), the ability of a firm to adopt innovative processes, but deliver few product innovations (Camisón & Villar-López, 2014). Therefore, in situations of disruptive innovations, small emergent companies have an advantage over the large incumbents because leaders may change the organization and processes quickly to take advantage of the new market or application, even without fully maturing the new product (Christensen, 1997). A business leader's awareness of the company situation and innovation cycle will have a better probability of guiding his organization to capitalize on opportunities.

Enkel, Heil, Hengstler, and Wirth (2017) studied exploitative and explorative market conditions, concluding that disruptive or radical innovations were more likely to emerge from exploratory research activities, whereas exploitative research would result in incremental or sustaining innovations. Individuals in organizations may find it challenging to be competent in both exploratory and exploitative skills, as these are very different disciplines (Enkel et al., 2017). Leaders should ensure their organizations are ambidextrous, having both exploitative and explorative competencies, but should realize that exploitative and explorative innovation success has a high correlation to the leadership type, opening, and closing behaviors (Zacher, Robinson, & Rosing, 2016). Transformational leadership and open practices favor exploratory innovations, while transactional leadership and closing behaviors show a high correlation with exploitation strategies (Zacher et al., 2016). Companies that wish to be high performing in both radical and incremental innovations need to utilize both exploratory and exploitation strategies and be ambidextrous in leadership throughout the organization (Carayannis et al., 2015; Zacher et al., 2016).

Traditionally, the development of innovation and new ideas are the purview of guarded and highly secretive research and development departments within large corporations, government laboratories, and military institutions. Complex legal structures evolved to protect intellectual property, including patents, copyrights, trademarks, trade secrets, and corporate know-how protections (Cockburn & Long, 2015). As markets matured, innovation demand gradually shifted away from technical innovation and toward market and process innovations to satisfy steadily increasing market pressures for greater flexibility and rapid delivery (Brem et al., 2016). Leaders reacted by expanding their innovation idea search and seeking closer cooperation with companies throughout the entire supply chain, by that increasing the process expertise and using the supply chain as part of the development process (Shenhar et al., 2016). The existing structure is advantageous to large, incumbent companies who had internal competencies in the currently dominant technologies and extensive supply chains for advantage.

Many disruptive innovations enter through small, entrepreneurial companies that have neither the advantage of size, maturity, or access to the dominant technologies that incumbents possess (Christensen, 1997; Utterback, 1996; Velu, 2015). These emerging companies may rely on open innovation networks and innovation clusters to diffuse innovations (Engel, 2015). For the cluster of companies to be effective for innovation, there has to be more than just industry or geographical specialization, there also has to be rapid emergence of commercialization and opening of new markets (Engel, 2015; Ferras-Hernandez & Nylund, 2019). Coinnovation is a process involving the enterprise, suppliers, outside knowledge providers, and even competitors (Frow et al., 2015). Cocreation is an extension of the coinnovation concept, with the involvement of the customer in the process of developing or producing the innovative product (Fernandes & Remelhe, 2016; Frow et al., 2015). Cocreation has the benefit of strengthening the brand relationship with the consumer, enhancing the knowledge and engagement of the company, supply chain, and other stakeholders (Frow et al., 2015). In an entirely cocreative environment, companies may not be able to secure and protect innovation intellectual property (Frow et al., 2015).

The innovation management strategies for business leaders may be different in large, mature companies from those in small entrepreneurial firms. Business leaders with a clear understanding of how the dependent variables of age and size affect innovation success probability, as well as how the additional variable of culture may influence the likelihood, were better equipped to organize their resources in the most effective manner possible. There is no single best answer; each leader must find the business approach suited to their company and market situation.

Transition

Forecasting the effects of innovation in complex market environments is ambiguous and indeterminate. Many variables positively correlate with innovation success, but causality is difficult to determine. Innovation is an essential driver of economic growth and future planning for company management and a critical strategic tool for most businesses. Leaders need to understand what the industry norms are for incremental and semiradical innovations, and how the types of semiradical innovation can influence the rate of revenue growth. Also, leaders need to understand how the company size, expressed as annual revenue, age, and origin, affect the likelihood of successful commercialization of semiradical innovations. The relationships may allow leaders at all organizational levels to plan and implement the tactics and organizational structures that have higher probabilities of achieving innovation-driven revenue growth.

In Section 2 of the study, I detailed the methodology chosen for the study and the rationale for selecting the particular methods. Explanation of the data collection and sampling methods used in the study was in Section 2, as well as an analysis of study validity and reliability. Also, in Section 2, I explained the role of the researcher and any participants in the study.

Section 3 of the study contains a presentation of the quantitative results of the study. The hypotheses derived from the research question addressed using appropriate statistical methods and results were discussed within the view of the theoretical framework. Implications for professional practice and society, as well as recommendations for future research and investigation, are included in Section 3.

Section 2: The Project

Purpose Statement

The purpose of this quantitative correlational study was to examine the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth. The independent variables were company culture, company maturity, and total annual company revenue. The dependent variable was the annual revenue growth driven by innovations. The population was multinational, heavy equipment manufacturing companies operating globally from 2002 through 2018. The implications for positive social change include the potential to assist heavy equipment company leaders to better leverage R&D investments for improvement of infrastructure in an efficient and environmentally sound manner (Adams et al., 2016; Kuzemko et al., 2016).

Role of the Researcher

As the researcher in the study, I was responsible for the collection, organization, cleaning, and analysis of all the data used in the study from a variety of secondary sources. The use of secondary data in quantitative research is common, even if the data were compiled initially to answer a different research question (Fouché & Bartley, 2016). I was familiar with the heavy equipment industry and companies working in this industry, having been employed by various multinational heavy equipment companies for over 25 years. The top companies listed in the secondary data source for the study, the *Yellow Table*, were all known to me either as an employer or competitor. The secondary data gathered for the statistical analysis were from publicly available sources (see Sleight, 2013), mitigating the possibility of unconscious bias toward any of the participant companies.

The Belmont Report from 1979 provides research guidelines to ensure human subjects of research receive ethical treatment and that disadvantaged groups are adequately protected (Office of the Assistant Secretary for Health, n.d.). The current study design did not require the use of human subjects through interviews, surveys, or experiments. Therefore *The Belmont Report* guidelines regarding human subjects were satisfied. For this study, the raw data were available in public records as released by the companies in financial reporting statements.

Participants

The study sample was the annual list of the top 50 revenue companies in the global construction equipment industry, as presented by KHL publications in the annual *Yellow Table* from 2002 to 2018. The study did not require the use of any individual participants; therefore, considerations of recruiting and protecting classes of participants did not apply. To capture the innovation-driven revenue growth over the innovation cycle, it was necessary to capture longitudinal data covering as many innovations cycles as possible. The collection of primary revenue data for this study was impractical given the multiyear collection period. Secondary data are suitable for studies in which the researcher lacks the time or resources to collect the data and to improve the analytical capability to study rare events or long-term trends (Bainter & Curran, 2015; Johnston, 2017).

Research Method and Design

Research Method

Researchers use quantitative methodologies to examine the mathematical relationships between variables (C. Y. Lee et al., 2017), so quantitative methodologies were suitable for this study. I used archival data for the period from 2002 to 2018 to analyze the statistical correlation between innovation-driven revenue growth rates and three variables in multinational heavy equipment companies. Researchers use qualitative methodology when they intend to explore the meanings of a phenomenon and the feelings within the target population (Barnham, 2015; Carayannis et al., 2015; Pruitt, 2017), and mixed-methods research has qualitative descriptions validated with quantitative analysis (McCusker & Gunaydin, 2015; Pruitt, 2017). Because I did not explore the meanings or feelings associated with innovation-driven revenue, neither qualitative nor mixed-methods approaches were suitable.

Research Design

Researchers use correlational designs to examine the relationships between variables, but do not assign a particular theory or explanation for the relationship to avoid any implication of causality (Curtis, Comiskey, & Dempsey, 2016; Kim & Steiner, 2016; McCahill, Garrick, Atkinson-Palombo, & Polinski, 2016). In nonexperimental designs, there is no possibility to manipulate the independent variables or study participants as would be appropriate in experimental designs (Curtis et al., 2016; McCahill et al., 2016; Rovai et al., 2013). In the current study, I employed a nonexperimental correlational design.

Population and Sampling

The population comprised heavy equipment companies. The primary data set was the annual KHL International Construction top 50 lists of heavy equipment companies (Sleight, 2013), also known as the *Yellow Table*. I used the product categories, as published and maintained by the report editor, as the classification system to ensure consistency. KHL collects the data for the *Yellow Table* from company financial statements and other reliable sources and converts foreign currency to U.S. basis using current exchange rates (Sleight, 2013).

Nonprobabilistic sampling is a method in which the participants in the study are not chosen at random concerning the overall population (de Mello, Da Silva, & Travassos, 2015; Pruitt, 2017; Rovai et al., 2013). A nonprobabilistic sampling method was used in the study as the secondary data were taken from the *Yellow Table*, a stratified sampling frame that contains an annual listing of the top 50 construction equipment companies by revenue (see Sleight, 2013). The advantages of nonprobabilistic sampling are that researchers may have access to data that would be impossible to gather due to time, availability, or budgetary circumstances (Besharat, Langan, & Nguyen, 2016; de Mello et al., 2015; Etikan, Alkassim, & Abubakar, 2016). The disadvantages of nonprobabilistic sampling are that the sample may not be characteristic of the broad population because the sample is not truly random and may be subject to bias in sample selection (Etikan et al., 2016; Rovai et al., 2013; Sharma, 2017).

I employed availability sampling by utilizing all the samples in the *Yellow Table* from 2002 to 2018, where the companies had continuous data. Availability sampling is a nonprobabilistic sampling technique in which the researcher takes the samples based on availability or convenience (de Mello et al., 2015; Rovai et al., 2013; Sharma, 2017). The advantages of availability sampling are that the researcher may have access to samples that would be impossible to gather because of limited time or budget, and can also conduct longitudinal research on long-term phenomenon using archival data (Besharat et al., 2016; de Mello et al., 2015; Etikan et al., 2016). Availability sampling has the disadvantages of not being random and, therefore, being subject to bias in the sample selection (de Mello et al., 2015; Etikan et al., 2016; Sharma, 2017).

Statistical power is the measure of the statistical test to correctly reject the null hypothesis ($H_0 = \beta_1, \beta_2 \ldots \beta_m = 0$) and detect effects present that significantly differentiate the dichotomous variable (Osborne, 2014). If using 80% (0.80) power, a 20% chance exists that the researcher will mistakenly reject the null hypothesis and assume a difference between the groups when there was none in the general population. A type I, or alpha error, is the acceptable confidence level the researcher is willing to accept in which the null hypothesis was wrongly supported (Rovai et al., 2013). Power is complementary to type II, or beta errors (Power = 1-type II error), where the researcher accepts that the null hypothesis was wrongly rejected (Osborne, 2014).

Application of logistic regression and similar probability statistical techniques is influenced by medical and social sciences research, where type I errors are unacceptable because of the risk of treatment or exposure that may have no patient benefit (Akobeng, 2016; Hosmer et al., 2013; Osborne, 2014). In cases in which human health is at risk, professionals prefer to err toward no significant difference (use high power and accept type I error) until the evidence is overwhelming from multiple studies (Osborne, 2014). Although 80% is a commonly accepted power level for logistic regression statistical tests, this power level may still be unsuitable for binary tests for particular problems (Osborne, 2014). If a separate hypothesis exists for each variable in a multivariable analysis, the definition of power needs to be clear for each variable (Porter, 2017). Power can be set suitable to ensure the rejection of a false null hypothesis with any variable, referred to as 1-minimal (Porter, 2017). Alternatively, complete power refers to the effect of at least a specific size being present in all outcomes (Porter, 2017). Binary logistic regression analysis implies a two-way decision system. The researcher can find support for the null hypothesis, concluding no difference between groups, with the type I error limit determining the statistical confidence. Alternatively, the researcher can find support for the alternate hypothesis, in which a significant difference exists, with confidence as described by the type II (beta) limit.

For the current study, power was set at 0.95, alpha and beta (type I and II errors) at 0.05, and odds ratio at 1.83 (30% probability of semiradical innovation predicted based on the 16-year average growth). I assumed an R^2 for the covariates of 0.50, which indicated an a priori sample size of 79 for two-tailed logistic regression, as calculated by G*Power software using Hsieh correction factors for multivariate logistic regression (see Hosmer et al., 2013). A priori estimates, including sample size estimates, have limited usefulness in logistic regression because of the curvilinear nature and possible nonnormal distributions (Hosmer et al., 2013; Osborne, 2014). Logistic regression produces higher power results with larger samples and continuous data (Osborne, 2014). In the current data set, approximately 850 samples were available, and I used all possible samples in which the data were continuous, as well as bootstrapping and extrapolation methods to extend the sample and close any data gaps where possible. Data imputation was not suitable because this method adds additional uncertainty from bias in the imputed values (see de Jong, Buuren, & Spiess, 2015).

Ethical Research

The study contained secondary data obtained from published lists, specifically the KHL *International Construction Yellow Table*. I gathered additional data from public SEC filings and company annual reports to assess historical events as needed and to fill in any missing data so that the records for companies were continuous for the study years 2002 to 2018. To safeguard the confidentiality and identities of participant firms in the study, I assigned a unique numerical code to each firm. All data collected for the study will be archived and available for 5 years from the publication date of the study. Walden University's Institutional Review Board approval number 11-01-19-0339686 was granted for this study.

Data Collection Instruments

The study included the use of secondary data. Secondary data collection has the advantage that the data were collected by an independent researcher who had no connection to the research question of the current study, which minimizes the chance of bias in data collection (Fouché & Bartley, 2016). Given that the data collection occurred before my study and over the long term, I had limited ability to modify or validate the secondary data for this study (see Fouché & Bartley, 2016). The secondary data source was the revenue data from 2002 to 2018 for the top 50 companies in the heavy equipment industry, as published annually by the KHL group in *International Construction* magazine. The *Yellow Table* lists the annual revenue in U.S. dollars of the top 50 construction equipment companies as reported in company public statements. The U.S. dollar is commonly accepted as a measure of international financial transactions (Costigan, Cottle, & Keys, 2017). KHL group has compiled data for the *Yellow Table* since 2002 from public company records and statements of the top 50 construction equipment companies in the world (Sleight, 2013).

The dependent variable for the study was revenue growth, based on U.S. dollar value. The annual revenue growth for each company on the list was converted to an annual percentage growth rate. The top 15% of the companies as ranked by percentage annual growth were designated as high growth companies and assigned a binary value of one; the remainder of the companies in the top 50 list demonstrated standard growth and were assigned a value of zero. The transformed binary nominal scale is suitable for logistic regression (Hosmer et al., 2013; Saunders & Kilvington, 2016), the technique chosen for the study. This approach was consistent with Rogers's diffusion of innovation theory, in which innovators and early adopters comprise the first 15% of buyers of innovations and buy before the steep rise in the innovation diffusion curve (see Chang et al., 2015; Rogers, 2003).

For each company in the data set, the maturity variable was calculated on an ordinal scale using years since founding, as reflected in company history statements. I employed a three-part ranking (a) companies in the top third of age range were mature,

(b) companies in the middle tier of ages were developing, and (c) the remaining companies were emergent. For the culture variable, a nominal scale was used, reflecting the country in which the corporate offices had been for most of the company's history.

No other data collection instruments were required for this study. All of the secondary data used were publicly available, requiring no permissions for use in this study. All of the data from secondary sources were raw data; all analyses were done within the study by me.

Data Collection Technique

The use of secondary data is growing in importance in social research, driven by the proliferation of high-quality data sets, as well as the cost and difficulties of collecting primary data (Punch, 2013; Rovai et al., 2013). The advantages of secondary data for a researcher are that the data may be readily available at low acquisition cost, the data may cover long time periods required for longitudinal research questions, and there is an interest by the publisher and users to quickly and continuously correct any errors or omissions (Bainter & Curran, 2015; Fouché & Bartley, 2016; Johnston, 2017; Rovai et al., 2013). Secondary data have disadvantages for researchers because the data may have been gathered for other research questions and may not be complete for the new study; the researcher cannot follow up, verify, or control the collection techniques; and the credibility of the raw data is supported only by the originating publishing source (Fouché & Bartley, 2016; Punch, 2013; Rovai et al., 2013).

All of the data used in the current study were secondary data retrieved from published industry association publications, published annual reports, and government statistics. Because the *Yellow Table* lists only the top 50 companies by revenue for each year, it may have been necessary to extrapolate data points or research other public data sources for missing years to maintain continuity for each listed company. The statistical techniques for this study were well established and suitable for this study, and the study had no participant interviews, so a pilot survey to test the validity of the study was not conducted.

Data Analysis

The research question for this study was the following: What is the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth?

H_0: There is no likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth.

H_a: There is a likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth.

Binary logistic regression is a regression technique used to determine the probability of obtaining a dichotomous dependent (binary categorical) variable, using logit transformations of a single or multiple independent variables (Hosmer et al., 2013; Osborne, 2014). Logistic regression was appropriate for the study as I defined a dichotomous dependent variable where year-over-year (YoY) revenue growth in the highest 15th percentile with a value of one, and lower YoY revenue growth was assigned a value of zero. This was supported by Rogers's diffusion of innovation theory, which theorizes that innovators and early adopters comprise the first 15% of innovation buyers and engage before the steep rise in the innovation diffusion curve (Chang et al., 2015; Rogers, 2003).

Rogers's theory on the diffusion of innovation follows a nonlinear sigmoid function or S-curve (Mannan, Nordin, Rafik-Galea, & Ahmad Rizal, 2017; Rogers, 2003). Logistic regression is the preferred technique for functions that are curvilinear over conventional multivariate regression techniques as logistic regression uses an iterative maximum likelihood estimation rather than calculated ordinary least squares technique to determine the best fit to the sample data (Osborne, 2014). The maximum likelihood estimation methods allow a curvilinear shape to the logit, whereas the ordinary least squares only considers a linear best fit (Osborne, 2014).

An alternative and commonly used method for binary statistical analysis is discriminant function analysis (Osborne, 2014). Discriminant factor analysis uses a variation of ordinary least squares regression to produce an equation with a coefficient for each variable to predict the value of the binary dependent variable (Hosmer et al., 2013). The probabilities in a discriminant function analysis can be outside the range of zero to one, and the residuals may be heteroscedastic, meaning that the variability may not be uniform across all variable values (Osborne, 2014). For these reasons, the newer logistic regression methods are considered a replacement for discriminant function analysis and superior statistical treatment (Osborne, 2014). Probit regression is a methodology very similar to logistic regression, using the cumulative area under the normal distribution curve and converting the corresponding *z*-score to a probability (Osborne, 2014). Both probit and logit techniques suit curvilinear functions, such as the innovation diffusion and industry life cycle curves, and are different only in their derivation and historic application (Osborne, 2014). Logit functions have flatter tails in comparison to probit functions, meaning assumed distributions have more occurrences at the extremes (Klieštik, Kočišová, & Mišanková, 2015). The study includes the use of logistic regression with logit function, as the dependent variable of innovation-driven revenue growth will tend to fall into the extremes.

Logistic regression uses the natural logarithm of the *OR*, called the logit, to transform nonlinear distribution into a linear representation (Hosmer et al., 2013; Osborne, 2014). The regression equation using the logit for a single independent variable is: $g(x) = \beta_0 + \beta_1 x_1$ with the regression coefficient β_0 for the dependent variable indicating the intercept, and β_1 is the beta regression coefficient for the independent variable x_1 (Klieštik et al., 2015; Osborne, 2014). The regression coefficient for the independent variable indicates the effect of the variable and the slope of the best fit line for that variable. For a multivariable regression with *m* independent variables, the regression formula is:

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \cdots + \beta_m x_m. \quad (1)$$

Logistic regression is a nonparametric statistical test, not subject to the assumptions of a normal distribution, linearity, or equal variance across groups (Osborne, 2014; Pruitt, 2017). Logistic regression is sensitive to the accuracy of the data and very sensitive to missing data, especially nonrandom missing data (Osborne, 2014). The companies included in the top 50 listings may vary as revenues change and may cause a nonrandom discontinuity in the listing of companies. Given the sensitivity of logistic regression to missing data, the continuity of the revenues for every sampled company is necessary for the test validity. Cases where the secondary data are missing and not available from other public sources were considered outliers and not used in the study analysis. Additional assumptions in logistic regression are that the dependent variable is either binary or ordinal; that the samples are independent; that there is little multicollinearity in the data; that there is linearity between the independent variables and log odds; and that a large sample size is available (Osborne, 2014). For this study, I converted the dependent variable into a binary (0,1) by the top 15% of the rate of growth of innovation revenue. As the data was a set of data from 50 different companies each year, it was reasonable to assume the data was independent and has no multicollinearity. Linearity between the independent variables and the odds ratio was verified during the test. As large a sample size as available (2002 to 2018) of continuous data made up the data set for the study.

Data cleaning is the process of identifying and correcting imperfections in the raw study data (Greenwood-Nimmo & Shields, 2017). Imperfections in the data can come from measurement errors, coding errors, inconsistent measurement frequency or units, and duplicate entries (Greenwood-Nimmo & Shields, 2017). To minimize the chances of measurement, coding, or duplicate entries, I reviewed the data to ensure continuity in the companies used and verify or eliminate outliers in the data. All the raw data used in this study was from secondary sources, reported on an annual basis, and in U.S. dollars, eliminating the need for additional actions due to measurement errors arising from inconsistent frequency measures or units. Data cleaning is a process that requires judgment by the researcher (Greenwood-Nimmo & Shields, 2017). The study includes documentation of any actions and decisions in cleaning the raw data to present the changes within the study.

SPSS version 25 was used to generate the logistic regression and output parameters. SPSS output consists of the regression coefficients, the beta (β) for each of the variables which indicate the effect of that variable, or the slope of the line attributable to that variable (Osborne, 2014; Pruitt, 2017). The standard error (*S.E.*) of the beta estimate is a measure of the precision of the estimate, a high *S.E.* for any variable beta indicates low precision (Osborne, 2014). SPSS also lists the degree of freedom (*df*) for each of the variables, which shows the number of values that can vary in the calculation (Allen, 2017; Osborne, 2014). The SPSS output tables also give the odds ratio (*OR)*, the ratio of the probability (P_0) of the regression coefficient with a value of zero divided by the probability (P_1) of the coefficient being other than zero (Hosmer et al., 2013; Osborne, 2014). The output parameters also list the 95% confidence interval for the odds ratio, which gives the range of values for the odds ratio that we can be 95% certain that the actual unknown value fits within (Osborne, 2014).

The Wald statistic is a measure of the precision of the β constant for any independent variable and is calculated as the square of the β constant divided by the standard error (Osborne, 2014): Wald = $(\beta_m/SE)^2$. For a univariate regression, the Wald statistic is close to the overall chi-square statistic (Osborne, 2014). In cases of multivariable regression, such as in this study, the Wald test results must be consistent for all the independent variables to allow a relevant conclusion on the contribution of the variables (Hosmer et al., 2013). The Wald test statistic for each variable in the study indicates the goodness of fit of each model.

In ideal conditions, quantitative researchers prefer full experimental or quasiexperimental designs where the variables are controlled and manipulated in the experiment. Unfortunately, much of business, education, and social research is not possible under experimental conditions, as manipulation of the variables would be impossible, unethical, or financially prohibitive. Clinical researchers realize that the benefits of a controlled laboratory environment differ from actual conditions, prompting a gradual shift away from judging validity solely on study design (Kelly, Fitzsimons, & Baker, 2016). However, using nonexperimental, observational design exposes the research to validity issues, which can only be minimized by careful control of bias and future replication of the study results (Sulaiman et al., 2016).

Study Validity

For quantitative research, validity is classified as internal and external validity (Rovai et al., 2013). Internal validity is the extent that a change in the independent variable produces the observed effect in the dependent variable (Punch, 2013; Rovai et al., 2013). I used no participants or surveys in this study. Therefore the threats to internal validity as a result of history, maturation, testing, selection, halo effects, mortality, and compensation are eliminated (Rovai et al., 2013).

Three areas of concern remain regarding the internal validity of this study. Statistical conclusion validity is the extent to which the statistical treatment delivers the proper decision regarding type I error (Fox & Lash, 2017; Rovai et al., 2013). Conclusion validity is optimized in this study by using as large a sample as available and by application of modern logistic regression techniques (Osborne, 2014). The selection of the sample was a concern as this study uses a convenience sample reflecting the top 50 companies in the industry. Knowing that innovation is a driver of growth (Hausman & Johnston, 2014), I would expect the top 50 growth companies would have a higher proportion of firms engaged in innovation. For this reason, although the sample chosen may not reflect the total population of the equipment companies, the inferences toward innovation by high performing companies may be satisfied. Third, the study uses the rate of revenue growth as a proxy measure of innovation effectiveness, supported by the literature (Audretsch et al., 2014; Coad et al., 2016; Ikeda & Marshall, 2016; Slater et al., 2014). Other measures of innovation effectiveness are subjective and not conducive to a quantitative study.

External validity is the extent to which the results of the study can be generalized to the general population (Rovai et al., 2013). The conclusions from this study are unique to the top 50 companies in the industry, as judged by total revenue. The findings of the study do not apply to any particular company as the data used was an aggregate of high performing companies in the industry.

Transition and Summary

Innovation is an essential driver of economic growth and future planning for leaders. Leaders need to understand what the industry norms are for incremental and semiradical innovations, and how the types of semiradical innovation can influence the rate of revenue growth. Leaders need to understand how the company size, expressed as annual revenue, age, and origin, affect the likelihood of successful commercialization of semiradical innovations. The deliverable of this study was an examination of the relationships between the independent and dependent variables, and how the variables correlate to the types of innovation brought to market by leading, average, and trailing companies with the global heavy equipment industry. The relationships will allow leaders at all organizational levels to plan and implement the tactics and organizations that can deliver the required innovations to achieve the desired objectives.

The methodology chosen for the study was a multivariate logistic regression to examine how company age, origin, and size (annual revenue) influence semiradical innovations. I used secondary data over 16 years gathered from industry sources and did not conduct interviews for the study.

Section 3 of the study contains the detailed results of the statistical tests and the implications leaders regarding semiradical and incremental innovations in high performing global equipment companies. I tested and reported on the goodness of fit for the relationships, based on the study dependent variables. Section 3 also contains a discussion of the significance of the study for business leaders and society and the implications and suggestions for future studies.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth. Frequencies and percentages were examined to describe the trends in the nominal-level variables. To answer the research question, a binary logistic regression analysis was conducted. Statistical significance was interpreted at the generally accepted level, $\alpha = .05$. The binary logistic regression model for the overall growth of innovation-driven revenue showed no significant relationship between the dependent and independent variables, supporting the null hypothesis.

Presentation of the Findings

The research question for this study was the following: What is the likelihood of company culture, company maturity, and total annual company revenue predicting innovation-driven revenue growth?

Hypotheses

H_0: There is no likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth.

H_a: There is a likelihood of company culture, company maturity, and total annual company revenue predicting the innovation-driven yearly revenue growth.

Testing of Assumptions for Logistic Regression

The integrity of the logistic regression results depends on eight underlying assumptions, four related to the study design and four to the dataset (Hosmer et al., 2013; Osborne, 2014):

1. dichotomous dependent variables,
2. one or more independent variables that may be continuous or nominal,
3. independence of observations,
4. mutually exhaustive and exclusive nominal categories for all variables,
5. linear relationship between any continuous independent variables and the logit transformation of the dependent variable,
6. lack of multicollinearity,
7. no significant outliers or highly influential points, and
8. a large number of samples.

As detailed in Section 2, the design of this study included a dependent variable that was expressed as a dichotomous value, represented as 1 for innovative companies and 0 for not highly innovative companies. The independent variables were unrelated nominal variables with category choices that included all possible cases, so Assumptions 2, 4, and 5 were satisfied. Observations for the sample points are done yearly for each of the 50 companies in the *Yellow Table*, so Assumption 3 was confirmed.

Multicollinearity, Assumption 6, occurs when two or more of the independent variables are related to each other, making it impossible to isolate any statistical effects (Hosmer et al., 2013). To check for multicollinearity, I ran a linear regression using SPSS

Version 25 on the nominal independent variables of maturity, culture, and company annual revenue. A variance of inflation (VIF) value was calculated for each independent variable. A VIF value greater than 3 indicates the likelihood of multicollinearity between the variables (Thompson, Kim, Aloe, & Becker, 2017). Tables 1, 2, and 3 present the VIF values for the three independent variables. No VIF values exceeded 3; therefore, there was no evidence of multicollinearity in this data set.

Table 1

Collinearity Diagnostics Using Company Size as the Dependent Variable

	Collinearity statistics	
Variable	Tolerance	VIF
Company maturity	.847	1.181
Company culture	.847	1.181

Note. The dependent variable was company annual revenue.

Table 2

Collinearity Diagnostics Using Company Maturity as the Dependent Variable

	Collinearity statistics	
Variable	Tolerance	VIF
Company annual revenue	.942	1.062
Company culture	.942	1.062

Note. The dependent variable was company maturity.

Table 3

Collinearity Diagnostics Using Company Culture as the Dependent Variable

	Collinearity statistics	
Variable	Tolerance	VIF
Company annual revenue	.999	1.001
Company maturity	.999	1.001

Note. The dependent variable was company culture.

The final two assumptions, outliers and large sample sizes, were assessed from the data set available. No outliers were detected in the data set from the SPSS analysis. Logistic regression also depends on large sample sizes (Osborne, 2014). The G*Power analysis in Section 2 indicated a sample size of at least 79 points, and the data set from the *Yellow Tables* for the 16 years contained over 850 points. However, the samples were not independent because many of the companies in the *Yellow Table* were listed over multiple years and the sample points were related to the independent variables. Once I eliminated companies for which continuous data could not be ensured, the sample size consisted of 50 companies spanning 5 years. The sample size was smaller than the desired sample size recommended by G*Power and the literature for logistic regression considering three independent variables with eight degrees of freedom (see Hosmer et al., 2013). The reduced sample size meant the study was underpowered, which increased the likelihood of type I error in which the null hypothesis of no relationship would be supported even if a relationship existed in the general population. The study results must be judged with caution due to the small sample size.

Descriptive Statistics

The sample consisted of secondary data from 50 companies. The descriptive statistics are presented in Table 4.

Table 4

Frequency Distribution for Nominal Variables

Demographic	*n*	%
Company culture		
China	8	16.0
Europe	15	30.0
Japan	13	26.0
North America	8	16.0
Rest of world	6	12.0
Company revenue		
Large	14	28.0
Midsize	14	28.0
Small	22	44.0
Company maturity		
Developing	19	38.0
Emergent	15	30.0
Mature	16	32.0
Company growth (2008-2018; overall)		
Yes	9	22.0
No	41	78.0

A histogram of the dependent variable (rate of growth due to innovation) is shown in Figure 4. Companies with low or negative mean growth rates constituted most of the scores, with growth rates normally distributed between -20% and +50% annual growth. From the literature, I expected about 15% of the companies to be in high growth, or 7 to 8 companies from a sample of 50. Only two companies in the sample set, or 4% of the sample, achieved growth rates of over 20%, which may have indicated a lower rate of semiradical or radical innovations in this industry.

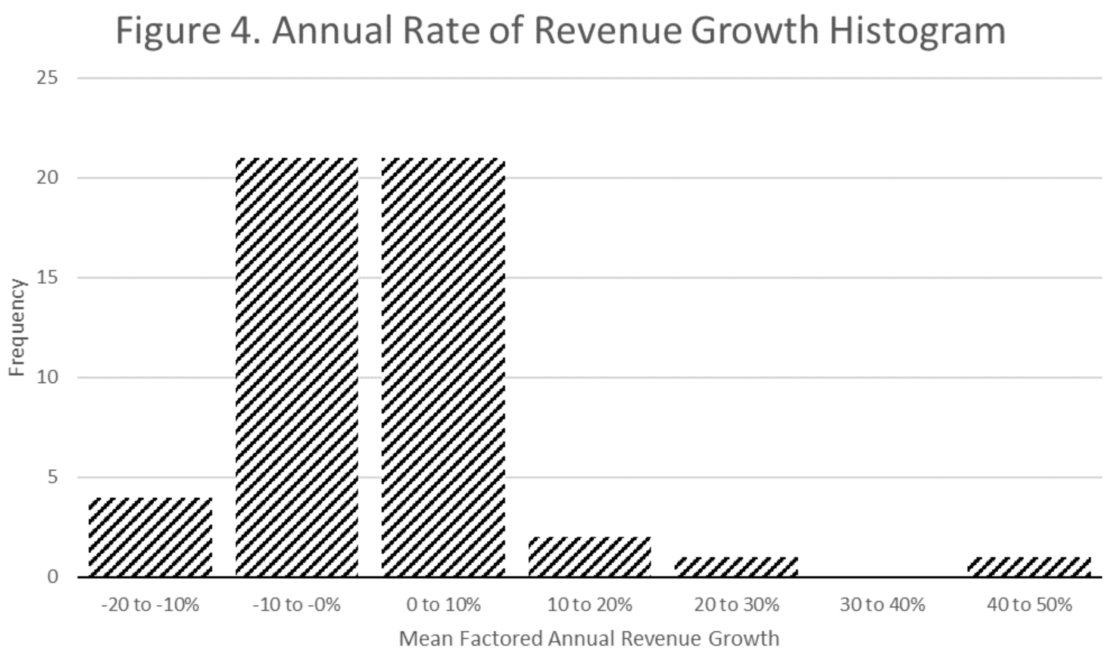

Figure 4. Mean factored annual revenue growth rates from 2014 to 2018 for *N* = 50 sample companies. Overall regional market growth rates factored out.

Inferential Results

A binary logistic regression model was used to examine whether company culture, company maturity, and total annual company revenue predicted annual innovation-driven revenue growth. A binary logistic regression is appropriate when assessing the strength of the predictive relationship between a group of predictors and a dichotomous outcome variable (Hosmer et al., 2013; Osborne, 2014). Five years of continuous data covering 2014 to 2018 on the 50 selected companies were used to construct the logistic regression model for overall growth.

Overall Growth

The overall regression model was not statistically significant, $\chi^2(8, N = 50) = 8.84$, $p = .356$, suggesting that the company culture, total avenue revenue, and maturity were not significant predictors of annual innovation-driven revenue growth (overall). The model correctly classified 84.0% of cases, which was a decrease of 2% of correct classifications compared to when the predictor variables were not included (Block 0). Approximately 16.2% (Cox and Snell R^2) to 29.2% of the variance (Nagelkerke R^2) in revenue growth (overall) could be explained by the predictor variables. The Hosmer Lemeshow goodness of fit test for overall growth was $\chi^2(8, N = 50) = 1.51$, $p = .993$, confirming that the model was not significant ($p > 0.05$) and therefore not a good fit to the predicted values. The analysis indicated that company size, maturity, and culture were not significantly associated with the innovation-driven revenue growth in heavy equipment companies. Table 5 contains a summary of the results of the regression model for revenue growth.

Table 5

Logistic Regression Results With Company Culture, Total Avenue Revenue, and Maturity Predicting Annual Innovation-Driven Revenue Growth (Overall)

Variable	*B*	*SE*	Wald	*p*	*OR*	*95% CI* Lower	Upper
Maturity (reference: Emergent)							
Developing	-1.21	1.80	0.45	.502	.298	.01	10.18
Large	1.50	1.56	1.81	.178	8.11	.01	4.42
Company culture (reference: N.A.)							
Europe	-20.72	13081.07	0.00	.999	.000	.00	--
China	-1.57	2.04	0.59	.443	.209	.00	11.42
Japan	1.40	1.41	0.99	.321	4.06	.26	64.52
Rest of world	-1.24	1.76	0.50	.481	.290	.01	9.06
Total annual revenue (reference: Small)							
Midsize	0.78	1.36	0.32	.569	2.18	.15	31.53
Large	2.09	1.56	1.81	.178	8.11	.39	170.81

Note. $X^2(8, N = 50) = 8.84$, $p = .356$, Cox and Snell $R^2 = 0.162$, Nagelkerke $R^2 = 0.292$.

Theoretical Discussion of Findings

The theoretical framework for the quantitative study was based on two theories (a) Rogers's (2003) diffusion of innovation theory and (b) Christensen's (1997) theories on disruptive innovations. The rapid diffusion of innovations in the marketplace during the early adopter and early majority buying phases, and the corresponding high innovation-driven revenue growth rate in those phases, as predicted by Rogers's theory, was the basis for the dependent variable in the study. Both Rogers's and Christensen's theories, as well as numerous other supporting studies in the literature, supported the independent variables of the culture, size, and maturity of companies, which may influence the innovation diffusion (Beck, Lopes-Bento, & Schenker-Wicki, 2016; Beyene et al., 2016; Christensen, 1997; Christensen et al., 2018; Engel, 2015; C. Y. Lee et al., 2017; Petrakis, Kostis, & Valsamis, 2015; Rogers, 2003; Teece & Linden, 2017).

The model developed in the current study did not have significant goodness of fit, and there was no evidence for support of correlation between the dependent variable (rate of innovation-driven revenue growth) and the independent variables of company culture, company maturity, and annual company revenue. Therefore, the null hypothesis stating that there is no likelihood of company culture, company maturity, and total annual company revenue predicting the annual innovation-driven revenue growth was supported. The alternate hypothesis stating a relationship was rejected in this study. This finding is not consistent with much of the literature on innovation.

The assumptions for the statistical tests used in the study were satisfied, except for the sample size, which is an essential criterion in logistic regression analysis. Small sample sizes, as well as exceedingly large samples, can influence the findings and the validity of a logistic regression test (Hosmer et al., 2013; Osborne, 2014). In these cases, the test may wrongly support the null hypothesis, a type I error, due to the high power required to support a statistically significant relationship (Hosmer et al., 2013). Due to the limited secondary data set and a relatively small number of companies engaged in global heavy equipment manufacturing, a sufficient sample size as recommended in the literature (Hosmer et al., 2013; Osborne, 2014) and by G*Power could not be achieved.

There were only two companies out of the 50 (4%) in which the mean of innovation-driven growth fell outside the range attributable to incremental innovations. This result was well below the prediction of eight companies, based on the 15% high-growth innovation rate (Rogers, 2003). Because the study was designed to reflect all innovation types, including new products through mergers, this result was unexpected. The predicted value is important in logistic regression because the predicted value sets up the odds ratio used in the calculation of sample size (Hosmer et al., 2013). A small effect will require a much larger sample to detect at any given power level (Hosmer et al., 2013).

The variance between the observed frequency of highly innovative companies and the model prediction may be due to the industry. Heavy equipment manufacturing may be lagging in driving revenue through innovation in comparison to sectors like high tech or medical, where innovations quickly diffuse (Christensen, 1997; Coccia, 2017a; Ferras-Hernandez & Nylund, 2019). Innovation, especially semiradical and radical, may take years to manifest in the market before the tangible output is observed, and this time delay may vary between industries (Beck et al., 2016; Christensen, 1997; Rogers, 2003). With only 5 years of data included in the current study, the effect of innovations recently launched may not have been apparent. Also, difficulty in accurately measuring the outputs of innovation as detailed in the literature (Arora et al., 2016; C. Y. Lee et al., 2017) may have contributed to the nonsignificant findings.

Although the overall model is not significant, the analysis of the variables within the model yielded useful insights. The Wald statistic in logistic regression is similar to the Chi-square test for the overall model, but applied to the individual predictor variables. In this study, the significance of the Wald statistic on each of the variables in the model is nonsignificant ($p > 0.05$), meaning that none of the variables in the model are individually significant predictors of innovation-driven revenue growth. The odds ratio is an indicator of the change in probability of outcome with a unit change in the independent variable, all other variables being equal (Hosmer, Lemeshow, & Sturdivant, 2013). The odds ratio for Japanese-culture companies (*OR* = 4.06) indicates that these companies are 4.06 times more likely to have high innovation-driven growth. This finding is consistent with the literature on Japan and innovation, especially in large, mature enterprises (Ikeda & Marshall, 2016; Kang, Jang, Kim, & Jeon, 2019; Woodside, Bernal, & Coduras, 2016).

Similarly, the odds ratios for size variables are higher, suggesting that as the company size increases, the odds of a high innovation-driven growth result increase (*OR* for 2.18 for mid-size and 8.11 for large companies). This result is contrary to the literature, which suggests that smaller, entrepreneurial companies may have advantages in radical and semiradical innovation as they are unconstrained by existing systems, processes, and dominant technologies (Christensen, 1997; Forés & Camisón, 2016). The special variable effects must be judged with caution, as the sample size was too small to provide any significant results.

For heavy equipment companies originating in Europe, the study analysis produced a nonsignificant result for the Wald statistic (*p* = .999), a very high standard error (*S.E.* = 13,081.07), a lower confidence interval of .000, and no upper confidence limit. There are two possible explanations for this result, that there is multicollinearity between the independent variables or that the model has separation or quasiseparation on the particular variable (Hosmer et al., 2013). In checking the model assumptions for logistic regression, I eliminated the multicollinearity of the independent variables using linear regression on the independent variables and variance inflation factors. Separation occurs when the sample is too small for the number of variables and a low number of cases with the outcome present, resulting in a model that does not converge around the limit in the maximum likelihood estimation (Hosmer et al., 2013). The sample size overall is too small for the number of independent variables.

For the 15 European companies in the sample, four were mature, mid-sized companies, of which two overall high innovation-driven growth and the other two had low growth outcomes. Therefore, the odds of high or low growth are equal and undistinguishable based on the three independent variables. This result is called quasiseparation. When quasiseparation occurs, the model cannot determine the odds of an outcome based on the independent variables, and the model is not likely to converge on one or more of the variables (Hosmer et al., 2013). Although separation can generate odd numerical results for one or more variables, separation is a mathematical phenomenon and does not affect the overall model statistics (Hosmer et al., 2013; Mansournia, Geroldinger, Greenland, & Heinze, 2018).

The findings of the study indicating no statistically significant relationship between the variables may be accurate and reflect reality, even though contrary to the literature. The design of statistical tests in quantitative research bias the tests to err on the side of the null hypothesis and possibly produce a type I error, rather than support a relationship where none exists (Osborne, 2014). Although an insufficient sample size may drive the nonsignificant finding, it is also possible that no significant effect would have been detected in the heavy equipment industry, even with a larger sample.

Application to Professional Practice

The findings of the study showed that the relationships between company culture, company maturity, and total annual company revenue were not significant in predicting the yearly innovation-driven revenue growth in global heavy equipment companies. This finding is contrary to the consensus in the literature (Arora et al., 2016; Christensen, 1997; Ferras-Hernandez & Nylund, 2019; Kostis et al., 2018; Petrakis et al., 2015) and my expectations. Support for the null hypothesis of no relationship does not mean there is no relationship; rather than statistical significance at the desired power level in this study with this sample set could not be established. That the final sample size available from the *Yellow Tables* did not meet the recommended sample size for logistic regression with eight degrees of freedom may be a contributing factor for the lack of power to detect significant relationship effects. The sample size limitation may be unavoidable in the heavy equipment industry, due to the limited number of companies in the business. Leaders wishing to understand the dynamics of innovation growth may need to look toward similar, but larger industry segments, such as industrial manufacturing, for further insights.

The culture of innovating companies is widely considered a factor in innovation success (Christensen, 1997; Kostis et al., 2018; Petrakis et al., 2015; Woodside et al., 2016). Company leaders wishing to drive innovation growth need to continually balance the resources expended by their firm toward exploratory and exploitative innovations with what innovations they can access from network cooperation and partnerships (Carnes et al., 2017; Kostis et al., 2018; Petrakis et al., 2015). Entrepreneurial companies are considered more adept at pursuing partnerships and relationships but may be restrained by the culture (Carnes et al., 2017). The restraining effect of the culture may be especially prevalent in large, mature companies where there is a significant investment in existing processes and structures (Carnes et al., 2017; Christensen, 1997; Petrakis et al., 2015).

The literature is divided on the effect that the size of the company may have on innovation success. Larger companies have more resources to dedicate toward innovative products and services, but the effect of innovation as a percentage of revenue growth is much smaller for a large company (Arora et al., 2016; Carnes et al., 2017; Christensen, 1997). Countries with collectivist cultures, such as Japan, have national innovation systems supporting large, mature companies and are not focused on small entrepreneurial start-up companies (Woodside et al., 2016). Such countries may have an advantage in capital intensive, conservative industries such as heavy equipment manufacturing. However, overreliance on an existing, dominant technology may be a disadvantage when the next disruptive technology eventually appears (Christensen, 1997; Lee & Berente, 2013).

This study had three independent variables (a) company culture, (b) company maturity, and (c) company size, as determined by annual revenue. Company cultures are difficult and slow to change, and leaders cannot change the size or maturity of their companies. Given these limitations, leaders may need to consider establishing divisions, brands, or projects that are outside the parent company, so they can act in an entrepreneurial way with little risk to the parent company operations, yet continue to have access to the resources and knowledge of the parent company (Christensen, 1997; Christensen et al., 2018). If the study findings had been significant on these independent variables toward innovation-driven growth, leaders in the heavy equipment industry would have had a benchmark to consider when establishing these autonomous divisions. With no relationships supported, leaders will have to determine their direction based on other similar industries and studies detailed within the literature.

Implications for Social Change

The findings of the study did not reveal a significant relationship between company culture, company maturity, company size, and innovation-driven revenue growth. Nevertheless, innovation is occurring in all industries and will reshape society in a variety of ways, and leaders need to manage the changes. In sustainable companies, leaders must simultaneously meet societal, environmental, and economic needs (Lubberink et al., 2017). The societal demands driven by increasing population and urbanization require raw materials to be procured, processed, and shipped to cities where people live by a diminishing percentage of workers in the rural areas (Leimbach et al., 2017; United Nations, Department of Economic and Social Affairs, Population Division, 2019). In response to these new societal needs, innovative heavy equipment products featuring connected machines, remote control, automation, and electric drives replacing fossil fuel internal combustion engines are emerging in the market. Workers trained in the operation and repair of traditional heavy equipment will need retraining, and new workers with the skills required for remote operating, diagnostics, and repair will need to be hired for the latest technology products (Chiva et al., 2014; Lubberink et al., 2017). The implications for positive social change from this study on innovation include the opportunity for leaders to embrace the new technologies, train, and equip future workforces to be ready to thrive in future environments, irrespective of the company culture, size, or maturity level.

Recommendations for Action

The results of this study could be of interest to leaders in global heavy equipment companies looking to take advantage of innovation opportunities. Although leaders cannot directly influence the variables of age, size, or origin of their companies, a better understanding of the relationships of these variables to the revenue growth from innovations may enable leaders to enact strategies to maximize innovation returns. Leaders that are complacent or overdependent on existing systems, products, and technologies, regardless of how successful, may not recognize innovations that either replace existing products or create new opportunities (Christensen, 1997; Teece & Linden, 2017). The proactive actions leaders may initiate include running autonomous

R&D management structures outside of the usual company processes, reporting, and capital structures; running new innovations and developments under a different brand; retooling manufacturing operations to take advantage of characteristics of the innovation, and targeting marketing efforts to new customers or applications (Christensen, 1997; Coad et al., 2016; Coccia, 2017a; Cohen & Caner, 2016; Engel, 2015; Ikeda & Marshall, 2016).

Scholars and practitioners may use the findings from this doctoral study to examine how traditional heavy equipment company organizations may need to change and adapt toward more rapid and aggressive innovation cycles, such as those employed for innovation in high-tech industries (Christensen et al., 2018). Leaders in traditional industrial companies need to learn and migrate to new models and processes based on successes in coinnovation, coinvention, and cocreation from more progressive industries (Fernandes & Remelhe, 2016; Frow et al., 2015). Implementation of these structures and processes in traditional industries will require a willingness to embrace the new processes, and development of company cultures receptive to the new paradigms. I intend to publish the results of this doctoral study in the ProQuest/UMI dissertation database through Walden University so that future researchers may build on the knowledge gained. The learnings from the study will be presented when applicable in seminars, conferences, and presentations, and I intend to use the methodology developed for this study on other secondary data from similar industry segments to ascertain if relationships are present in those cases.

The study did not show a significant relationship between the independent and dependent variables but also does not disprove possible relationships. There is consensus in the literature that such relationships do exist. The results of this study indicate that the effects of these correlations may be challenging to isolate and detect, especially in conservative industries such as heavy equipment manufacturing, and due to the limited populations and sample data available. As a practicing leader in the heavy equipment industry, I will continue to research this question.

Recommendations for Further Research

In this study, I examined the relationship between maturity, culture, and size and innovation-driven revenue growth in global heavy equipment companies from 2015 to 2018. There were two limitations identified for this study. First, the secondary data for the quantitative analysis was drawn from the KHL *Yellow Table*, a listing of the top 50 heavy equipment companies' annual revenue. Although each annual listing of the *Yellow Table* listed only the top 50 companies, the *Yellow Table* listing identified over 90 companies engaged in heavy equipment manufacturing over the 2002 to 2018 period. I was confident that the revenue gaps in the data could be closed, and enough companies found to satisfy the sample requirements. However, during the data cleaning stage, I discovered that many of the newer entrants into the *Yellow Table* listing were foreign companies, some state-owned, which did not report annual revenue. Also, the recession in 2007 through 2009 drove consolidation in the industry; many of the companies that existed pre-2007 were merged after the recession. The cumulative result was that the number of companies available in the secondary data source was smaller than the recommended sample size for logistic regression for the estimated effect size. I recommend future studies expand beyond small industry segments like heavy equipment manufacturing and use more extensive secondary databases such as the Fortune 500 manufacturing index, which would allow for larger sample sizes and ensure the statistical assumptions are satisfied. Larger sample sizes may be divided into smaller industry subsegments, provided the sample size assumptions can be met.

Second, there was a study limitation in detecting the innovation revenue beyond incremental innovations. The assumption for the study was that incremental innovations and demographic revenue growth would affect all industry companies in any particular region in similar fashion and magnitude, and that the remainder of the growth could be attributed to semiradical or radical innovation. I recommend a series of case studies to verify that the high growth predicted from semiradical or radical innovations can be isolated and is close to 15%, as predicted in the literature across many industries (Rogers, 2003). Should the case studies provide evidence that the proportion of companies in conservative industries having high innovation-driven growth rates is significantly lower than 15%, then the sample size will need to be even greater to have significant and reliable results.

Reflections

My experience with the DBA doctoral study process at Walden University is very positive as the program is well organized and structured for student success. The doctoral study was challenging and took far longer than anticipated, although in part due to a high workload in my regular job. The doctoral process gave good exposure to learning through self-directed research and practice in scholarly writing techniques.

The goal of this doctoral study was to determine if there was a relationship between age, size, and origin of heavy equipment companies and innovation-driven revenue. My initial impression, based on the literature review, personal experience, and peer-reviewed studies, was that the independent variables chosen would influence the innovation-driven revenue and that a significant correlation could be defined. The findings from this study did not support a statistical relationship between the variables, although they do not disprove a relationship either. I was surprised to discover that, on average, there were only 4% of companies in the heavy equipment industry sector that had high innovation-driven revenue growth rates, far less than the 15% predicted by the literature.

Conclusion

The relationship between company culture, company maturity, company size, and innovation-driven revenue growth in global heavy equipment companies over the 5 years spanning 2014 to 2018 was the topic of this doctoral study. The independent variables were company culture as defined through the location of the parent company, company maturity, and company size as determined by average annual revenue. The dependent variable was innovation-driven growth. The null hypothesis was that there was no statistical relationship between the independent and dependent variables. The alternate hypothesis was that there was a statistical relationship using a statistical significance level of $\alpha = .05$. The findings of the study in the logistic regression model were that company culture, company maturity, and company size did not have a significant relationship with innovation-driven growth rates, supporting the null hypothesis. The sample size available in the secondary data for global heavy equipment companies did not meet the recommended sample size for logistic regression with three independent variables, eight degrees of freedom and a significance level of $\alpha = .05$. When sample sizes are too small, statistical analysis is designed to err toward the null hypothesis, that there is no relationship, which was the finding in this study. The findings of this study are inconsistent with previous research, although it is possible that in the heavy equipment industry, there is no significant relationship among the independent and dependent variables. Further research studies on larger sample sizes, and in a variety of industry sectors, are needed to examine further the relationship among these or similar variables to understand the influence of innovation on company growth.

References

Abdi, K., & Senin, A. A. (2015). Empirical study on the effect of organizational culture on organization innovation. *Asian Social Science*, *11*(23), 114. doi:10.5539/ass.v11n23p114

Adams, R., Jeanrenaud, S., Bessant, J., Denyer, D., & Overy, P. (2016). Sustainability-oriented innovation: A systematic review. *International Journal of Management Reviews*, *18*, 180-205. doi:10.1111/ijmr.12068

Akobeng, A. K. (2016). Understanding type I and type II errors, statistical power and sample size. *Acta Paediatrica*, *105*, 605-609. doi:10.1111/apa.13384

Alhaddi, H. A. (2016). An exploratory paper on strategy implementation: Industry look at some of the world’s most profitable and most innovative companies. *Journal of Management and Strategy*, *7*(4), 1. doi:10.5430/jms.v7n4p1

Allen, V. C. (2017). *Relationship between loan product, loan amount, and foreclosure after the subprime lending crisis* (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses database (UMI No. 10642410)

Ang, J., & Madsen, J. (2015). Imitation versus innovation in an aging society: International evidence since 1870. *Journal of Population Economics*, *28*, 299-327. doi:10.1007/s00148-014-0513-0

Arora, A., Cohen, W. M., & Walsh, J. P. (2016). The acquisition and commercialization of invention in American manufacturing: Incidence and impact. *Research Policy*, *45*, 1113-1128. doi:10.1016/j.respol.2016.02.005

Åstebro, T., & Serrano, C. J. (2015). Business partners: Complementary assets, financing, and invention commercialization. *Journal of Economics & Management Strategy*, *24*, 228-252. doi:10.1111/jems.12095

Audretsch, D., Coad, A., & Segarra, A. (2014). Firm growth and innovation. *Small Business Economics*, *43*, 743-749. doi:10.1007/s11187-014-9560-x

Bainter, S. A., & Curran, P. J. (2015). Advantages of integrative data analysis for developmental research. *Journal of Cognition & Development*, *16*, 1-10. doi:10.1080/15248372.2013.871721

Baranenko, S. P., Dudin, M. N., Lyasnikov, N. V., & Busygin, K. D. (2014). Use of environmental approach to innovation-oriented development of industrial enterprises. *American Journal of Applied Sciences*, *11*, 189-194. doi:10.3844/ajassp.2014.189.194

Barnham, C. (2015). Quantitative and qualitative research. *International Journal of Market Research*, *57*, 837-854. doi:10.2501/IJMR-2015-070

Beck, M., Lopes-Bento, C., & Schenker-Wicki, A. (2016). Radical or incremental: Where does R&D policy hit? *Research Policy*, *45*, 869-883. doi:10.1016/j.respol.2016.01.010

Besharat, A., Langan, R. J., & Nguyen, C. A. (2016). Fashionably late: Strategies for competing against a pioneer advantage. *Journal of Business Research*, *69*, 718-725. doi:10.1016/j.jbusres.2015.08.010

Beyene, K. T., Sheng, S. C., & Wei, W. W. (2016). Linking national culture and product innovation performance: What really influences the interplay, strategy formulation or implementation effectiveness? *International Journal of Business and Management*, *11*(2), 184-196. doi:10.5539/ijbm.v11n2p184

Brem, A., Nylund, P. A., & Schuster, G. (2016). Innovation and de facto standardization: The influence of dominant design on innovative performance, radical innovation, and process innovation. *Technovation*, *50*, 79-88. doi:10.1016/j.technovation.2015.11.002

Busse, C., Kach, A. P., & Wagner, S. M. (2017). Boundary conditions: What they are, how to explore them, why we need them, and when to consider them. *Organizational Research Methods*, *20*, 574-609. doi:10.1177/1094428116641191

Camisón, C., & Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research*, *67*, 2891-2902. doi:10.1016/j.jbusres.2012.06.004

Campanelli, A. S., & Parreiras, F. S. (2015). Agile methods tailoring: A systematic literature review. *Journal of Systems and Software*, *110*, 85-100. doi:10.1016/j.jss.2015.08.035

Carayannis, E. G., Sindakis, S., & Walter, C. (2015). Business model innovation as lever of organizational sustainability. *Journal of Technology Transfer*, *40*, 85-104. doi:10.1007/s10961-013-9330-y

Carnes, C. M., Chirico, F., Hitt, M. A., Huh, D. W., & Pisano, V. (2017). Resource orchestration for innovation: Structuring and bundling resources in growth- and maturity-stage firms. *Long Range Planning*, *50*, 472-486. doi:10.1016/j.lrp.2016.07.003

Chang, S. L., Kibel, A. S., Brooks, J. D., & Chung, B. I. (2015). The impact of robotic surgery on the surgical management of prostate cancer in the USA. *BJU International*, *115*, 929-936. doi:10.1111/bju.12850

Chiva, R., Ghauri, P., & Alegre, J. (2014). Organizational learning, innovation and internationalization: A complex system model. *British Journal of Management*, *25*, 687-705. doi:10.1111/1467-8551.12026

Choi, S. (2019). Supply chain performance analysis of Dow Jones Industrial Average indexed firms and top 50 supply chain firms. *Decision Sciences Journal of Innovative Education*, *17*, 33-52. doi:10.1111/dsji.12172

Christensen, C. M. (1997). *The innovator's dilemma: When new technologies cause great firms to fail* (1st edition). Boston, MA: Harvard Business Review Press.

Christensen, C. M., Dillon, K., Hall, T., & Duncan, D. S. (2016). *Competing against luck: The story of innovation and customer choice*. New York, NY: Harper Business.

Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. E. (2018). Disruptive innovation: An intellectual history and directions for future research. *Journal of Management Studies*, *55*(7), 1043-1078. doi:10.1111/joms.12349

Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy*, *45*, 387-400. doi:10.1016/j.respol.2015.10.015

Coccia, M. (2017a). Sources of technological innovation: Radical and incremental innovation problem-driven to support competitive advantage of firms. *Technology*

Analysis & Strategic Management, *29*, 1048-1061. doi:10.1080/09537325.2016.1268682

Coccia, M. (2017b). The source and nature of general purpose technologies for supporting next K-waves: Global leadership and the case study of the U.S. Navy's mobile user objective system. *Technological Forecasting and Social Change*, *116*, 331-339. doi:10.1016/j.techfore.2016.05.019

Coccia, M. (2018). A theory of the general causes of long waves: War, general purpose technologies, and economic change. *Technological Forecasting and Social Change*, *128*, 287-295. doi:10.1016/j.techfore.2017.11.013

Cockburn, I., & Long, G. (2015). The importance of patents to innovation: Updated cross-industry comparisons with biopharmaceuticals. *Expert Opinion on Therapeutic Patents*, *25*, 739-742. doi:10.1517/13543776.2015.1040762

Cohen, S. K., & Caner, T. (2016). Converting inventions into breakthrough innovations: The role of exploitation and alliance network knowledge heterogeneity. *Journal of Engineering and Technology Management*, *40*, 29-44. doi:10.1016/j.jengtecman.2016.03.002

Colombo, M. G., Franzoni, C., & Veugelers, R. (2015). Going radical: Producing and transferring disruptive innovation. *Journal of Technology Transfer*, *40*, 663-669. doi:10.1007/s10961-014-9361-z

Costigan, T., Cottle, D., & Keys, A. (2017). The US dollar as the global reserve currency: Implications for US hegemony. *World Review of Political Economy*, *8*(1), 104-122. doi:10.13169/worlrevipoliecon.8.1.0104

Curado, C., Muñoz-Pascual, L., & Galende, J. (2018). Antecedents to innovation performance in SMEs: A mixed methods approach. *Journal of Business Research*. doi:10.1016/j.jbusres.2017.12.056

Curtis, E. A., Comiskey, C., & Dempsey, O. (2016). Importance and use of correlational research. *Nurse Researcher, 23*(6), 20. doi:10.7748/nr.2016.e1382

de Jong, R., Buuren, S. van, & Spiess, M. (2015). Multiple imputation of predictor variables using generalized additive models. *Communications in Statistics - Simulation and Computation, 45*, 968-985. doi:10.1080/03610918.2014.911894

de Mello, R. M., Da Silva, P. C., & Travassos, G. H. (2015). Investigating probabilistic sampling approaches for large-scale surveys in software engineering. *Journal of Software Engineering Research and Development. 3*(1), 1-26. doi:10.1186/s40411-015-0023-0

Dean, J. (2014). Personal protective equipment. *Professional Safety, 59*(2), 41-46. Retrieved from http://www.asse.org/professionalsafety

Eggers, J. P., & Kaul, A. (2018). Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. *Academy of Management Journal, 61*, 67-93. doi:10.5465/amj.2015.1123

Ekdale, B., Singer, J. B., Tully, M., & Harmsen, S. (2015). Making change: Diffusion of technological, relational, and cultural innovation in the newsroom. *Journalism & Mass Communication Quarterly, 92*, 938-958. doi:10.1177/1077699015596337

Engel, J. S. (2015). Global clusters of innovation: Lessons from Silicon Valley. *California Management Review, 57*(2), 36-65. doi:10.1525/cmr.2015.57.2.36

Enkel, E., Heil, S., Hengstler, M., & Wirth, H. (2017). Exploratory and exploitative innovation: To what extent do the dimensions of individual level absorptive capacity contribute? *Technovation*, *60-61*, 29-38. doi:10.1016/j.technovation.2016.08.002

Etikan, I., Alkassim, R., & Abubakar, S. (2016). Comparison of snowball sampling and sequential sampling technique. *Biometrics and Biostatistics International Journal*, *3*(1), 55-56. doi:10.15406/bbij.2016.03.00055

Euchner, J. (2016). Business model innovation. *Research Technology Management*, *59*(3), 10-11. doi:10.1080/08956308.2016.1161396

Fedderke, J. W., & Liu, Y. (2017). Schumpeterian and semi-endogenous productivity growth explanations. *Economics of Transition*, *25*, 111-137. doi:10.1111/ecot.12114

Fernandes, T., & Remelhe, P. (2016). How to engage customers in co-creation: Customers’ motivations for collaborative innovation. *Journal of Strategic Marketing*, *24*, 311-326. doi:10.1080/0965254X.2015.1095220

Ferras-Hernandez, X., & Nylund, P. A. (2019). Clusters as innovation engines: The accelerating strengths of proximity. *European Management Review*, *16*, 37-53. doi:10.1111/emre.12330

Focacci, A. (2017). Controversial curves of the economy: An up-to-date investigation of long waves. *Technological Forecasting and Social Change*, *116*, 271-285. doi:10.1016/j.techfore.2016.10.008

Forés, B., & Camisón, C. (2016). Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? *Journal of Business Research*, *69*, 831-848. doi:10.1016/j.jbusres.2015.07.006

Fouché, C., & Bartley, A. (2016). Teaching data analysis to the data-averse: A framework for educators. *Journal of Teaching in Social Work*, *36*, 70-83. doi:10.1080/08841233.2016.1125231

Fox, M. P., & Lash, T. L. (2017). On the need for quantitative bias analysis in the peer-review process. *American Journal of Epidemiology*, *185*, 865-868. doi:10.1093/aje/kwx057

Frow, P., Nenonen, S., Payne, A., & Storbacka, K. (2015). Managing co-creation design: A strategic approach to innovation. *British Journal of Management*, *26*, 463-483. doi:10.1111/1467-8551.12087

Gao, Y., Li, Y., Cheng, M., & Feng, G. (2017). How does market learning affect radical innovation? The moderation roles of horizontal ties and vertical ties. *Journal of Business & Industrial Marketing*, *32*, 57-74. doi:10.1108/JBIM-11-2015-0215

Greenwood-Nimmo, M., & Shields, K. (2017). An introduction to data cleaning using Internet search data. *Australian Economic Review*, *50*, 363-372. doi:10.1111/1467-8462.12235

Grinin, L. E., Grinin, A. L., & Korotayev, A. (2017). Forthcoming Kondratieff wave, cybernetic revolution, and global ageing. *Technological Forecasting and Social Change*, *115*, 52-68. doi:10.1016/j.techfore.2016.09.017

Guisado-González, M., Vila-Alonso, M., & Guisado-Tato, M. (2016). Radical innovation, incremental innovation and training: Analysis of complementarity. *Technology in Society*, *44*, 48-54. doi:10.1016/j.techsoc.2015.08.003

Hausman, A., & Johnston, W. J. (2014). The role of innovation in driving the economy: Lessons from the global financial crisis. *Journal of Business Research*, *67*, 2720-2726. doi:10.1016/j.jbusres.2013.03.021

Hosmer, D. Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. Hoboken, NJ: John Wiley & Sons.

Ikeda, K., & Marshall, A. (2016). How successful organizations drive innovation. *Strategy & Leadership*, *44*(3), 9-19. doi:10.1108/SL-04-2016-0029

Johnston, M. P. (2017). Secondary data analysis: A method of which the time has come. *Qualitative and Quantitative Methods in Libraries*, *3*, 619-626. Retrieved from http://www.qqml.net/index.html

Kang, D., Jang, W., Kim, Y., & Jeon, J. (2019). Comparing National Innovation System among the USA, Japan, and Finland to Improve Korean Deliberation Organization for National Science and Technology Policy. *Journal of Open Innovation: Technology, Market, and Complexity*, *5*, 82. doi:10.3390/joitmc5040082

Katz, J. S. (2016). What is a complex innovation system? *PLOS ONE*, *11*(6), 1-24. doi:10.1371/journal.pone.0156150

Kelly, P., Fitzsimons, C., & Baker, G. (2016). Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. *International Journal of Behavioral Nutrition and Physical Activity, 13*, 32. doi:10.1186/s12966-016-0351-4

Kim, Y., & Steiner, P. (2016). Quasi-experimental designs for causal inference. *Educational Psychologist, 51*, 395-405. doi:10.1080/00461520.2016.1207177

King, A. A., & Baatartogtokh, B. (2015). How useful is the theory of disruptive innovation? *MIT Sloan Management Review*, *57*(1), 77. Retrieved from http//sloanreview.mit.edu/

Klieštik, T., Kočišová, K., & Mišanková, M. (2015). Logit and probit model used for prediction of financial health of company. *Procedia Economics and Finance*, *23*, 850-855. doi:10.1016/S2212-5671(15)00485-2

Kostis, P. C., Kafka, K. I., & Petrakis, P. E. (2018). Cultural change and innovation performance. *Journal of Business Research*, *88*, 306-313. doi:10.1016/j.jbusres.2017.12.010

Kowalkowski, C., Windahl, C., Kindström, D., & Gebauer, H. (2015). What service transition? Rethinking established assumptions about manufacturers' service-led growth strategies. *Industrial Marketing Management*, *45*, 59-69. doi:10.1016/j.indmarman.2015.02.016

Kuzemko, C., Lockwood, M., Mitchell, C., & Hoggett, R. (2016). Governing for sustainable energy system change: Politics, contexts and contingency. *Energy Research & Social Science*, *12*, 96-105. doi:10.1016/j.erss.2015.12.022

Lee, C. Y., Lee, J. H., & Gaur, A. S. (2017). Are large business groups conducive to industry innovation? The moderating role of technological appropriability. *Asia Pacific Journal of Management*, *34*, 313-337. doi:10.1007/s10490-016-9481-0

Lee, H., & Markham, S. K. (2016). PDMA comparative performance assessment study (CPAS): Methods and future research directions. *Journal of Product Innovation Management*, *33*, 3-19. doi:10.1111/jpim.12358

Lee, J., & Berente, N. (2013). The era of incremental change in the technology innovation life cycle: An analysis of the automotive emission control industry. *Research Policy*, *42*, 1469-1481. doi:10.1016/j.respol.2013.05.004

Leimbach, M., Kriegler, E., Roming, N., & Schwanitz, J. (2017). Future growth patterns of world regions - A GDP scenario approach. *Global Environmental Change*, *42*, 215-225. doi:10.1016/j.gloenvcha.2015.02.005

Levie, J., & Lichtenstein, B. B. (2010). A terminal assessment of stages theory: Introducing a dynamic states approach to entrepreneurship. *Entrepreneurship: Theory & Practice*, *34*, 317-350. doi:10.1111/j.1540-6520.2010.00377.x

Linstone, H. A. (2011). Three eras of technology foresight. *Technovation*, *31*, 69-76. doi:10.1016/j.technovation.2010.10.001

Lubberink, R., Blok, V., Van Ophem, J., & Omta, O. (2017). Lessons for responsible innovation in the business context: A systematic literature review of responsible, social and sustainable innovation practices. *Sustainability*, *9*, 721. doi:10.3390/su9050721

Mannan, S., Nordin, S. M., Rafik-Galea, S., & Ahmad Rizal, A. R. (2017). The ironies of new innovation and the sunset industry: Diffusion and adoption. *Journal of Rural Studies, 55*, 316-322. doi:10.1016/j.jrurstud.2017.07.015

Mansournia, M. A., Geroldinger, A., Greenland, S., & Heinze, G. (2018). Separation in Logistic Regression: Causes, Consequences, and Control. *American Journal of Epidemiology*, *187*, 864–870. doi:10.1093/aje/kwx299

Massiani, J., & Gohs, A. (2015). The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. *Research in Transportation Economics*, *50*, 17-28. doi:10.1016/j.retrec.2015.06.003

Mastrogiorgio, M., & Gilsing, V. (2016). Innovation through exaptation and its determinants: The role of technological complexity, analogy making & patent scope. *Research Policy*, *45*, 1419-1435. doi:10.1016/j.respol.2016.04.003

McCahill, C. T., Garrick, N., Atkinson-Palombo, C., & Polinski, A. (2016). Effects of parking provision on automobile use in cities: Inferring causality. *Transportation Research Record*, *2543*, 159-165. doi:10.3141/2543-19

McCusker, K., & Gunaydin, S. (2015). Research using qualitative, quantitative or mixed methods and choice based on the research. *Perfusion*, *30*, 537-542. doi:10.1177/0267659114559116

Nagy, D., Schuessler, J., & Dubinsky, A. (2016). Defining and identifying disruptive innovations. *Industrial Marketing Management*, *57*, 119-126. doi:10.1016/j.indmarman.2015.11.017

Nan, N., Zmud, R., & Yetgin, E. (2014). A complex adaptive systems perspective of innovation diffusion: An integrated theory and validated virtual laboratory. *Computational and Mathematical Organization Theory*, *20*, 52-88. doi:10.1007/s10588-013-9159-9

Nicolau, J. L., & Santa-María, M. J. (2015). Battle royal in biotechnology: R&D vs. product vs. process innovations. *Technology Analysis & Strategic Management, 27*, 503-516. doi:10.1080/09537325.2015.1012056

Office of the Assistant Secretary for Health. (n.d.). *The Belmont report*. Retrieved from https://www.hhs.gov/ohrp/

Osborne, J. W. (2014). *Best practices in logistic regression*. Los Angeles, CA: SAGE Publications, Inc.

Paré, G., Trudel, M.-C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information & Management*, *52*, 183-199. doi:10.1016/j.im.2014.08.008

Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing*, *27*, 91-106. doi:10.1016/j.ijresmar.2009.12.012

Peters, M. D. J., Godfrey, C. M. R., Khalil, H. Bp., McInerney, P., Parker, D., & Soares, C. B. R. (2015). Guidance for conducting systematic scoping reviews. *Journal of Evidence-Based Healthcare*, *13*, 141-146. doi:10.1097/XEB.0000000000000050

Petrakis, P. E., Kostis, P. C., & Valsamis, D. G. (2015). Innovation and competitiveness: Culture as a long-term strategic instrument during the European Great Recession. *Journal of Business Research*, *68*, 1436-1438. doi:10.1016/j.jbusres.2015.01.029

Pirgmaier, E. (2017). The neoclassical trojan horse of steady-state economics. *Ecological Economics*, *133*, 52-61. doi:10.1016/j.ecolecon.2016.11.010

Porter, K. E. (2017). Statistical power in evaluations that investigate effects on multiple outcomes: A guide for researchers. *Journal of Research on Educational Effectiveness*, *0*, 1-29. doi:10.1080/19345747.2017.1342887

Pruitt, H. (2017). *Predicting bank failure using regulatory accounting data* (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses database. (UMI No. 10622911)

Punch, K. F. (2013). *Introduction to social research: Quantitative and qualitative approaches*. Los Angeles, CA: SAGE Publications, Inc.

Rogers, E. M. (2003). *Diffusion of innovations* (5th edition). New York, NY: Free Press.

Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology? *Research Policy*, *44*, 1827-1843. doi:10.1016/j.respol.2015.06.006

Rovai, A. P., Baker, J. D., & Ponton, M. K. (2013). *Social science research design and statistics: A practitioner's guide to research methods and IBM SPSS*. Chesapeake, VA: Watertree Press LLC.

Salehi, F., & Yaghtin, A. (2015). Action research innovation cycle: Lean thinking as a transformational system. *Procedia - Social and Behavioral Sciences*, *181*, 293-302. doi:10.1016/j.sbspro.2015.04.891

Saunders, W. S. A., & Kilvington, M. (2016). Innovative land use planning for natural hazard risk reduction: A consequence-driven approach from New Zealand. *International Journal of Disaster Risk Reduction, 18,* 244-255. doi:10.1016/j.ijdrr.2016.07.002

Seifert, R. W., Tancrez, J.-S., & Biçer, I. (2016). Dynamic product portfolio management with life cycle considerations. *International Journal of Production Economics*, *171*, 71-83. doi:10.1016/j.ijpe.2015.10.017

Shannon-Baker, P. (2016). Making paradigms meaningful in mixed methods research. *Journal of Mixed Methods Research, 10,* 319-334. doi:10.1177/1558689815575861

Sharma, G. (2017). Pros and cons of different sampling techniques. *International Journal of Applied Research*, *3*, 749-752. Retrieved from http://allresearchjournal.com/

Shenhar, A. J., Holzmann, V., Melamed, B., & Zhao, Y. (2016). The challenge of innovation in highly complex projects: What can we learn from Boeing's dreamliner experience? *Project Management Journal*, *47*(2), 62-78. doi:10.1002/pmj.21579

Slater, S. F., Mohr, J. J., & Sengupta, S. (2014). Radical product innovation capability: Literature review, synthesis, and illustrative research propositions. *Journal of Product Innovation Management*, *31*, 552-566. doi:10.1111/jpim.12113

Sleight, C. (2013). Equipment top 50. *International Construction*, *52*(3), 13-16. Retrieved from https://www.khl.com

Snyder, H., Witell, L., Gustafsson, A., Fombelle, P., & Kristensson, P. (2016). Identifying categories of service innovation: A review and synthesis of the literature. *Journal of Business Research*, *69,* 2401-2408. doi:10.1016/j.jbusres.2016.01.009

Stockman, C. (2015). Achieving a doctorate through mixed methods research. *Electronic Journal of Business Research Methods*, *13*(2), 74-84. Retrieved from http://www.ejbrm.com

Suder, A., & Kahraman, C. (2015). Multicriteria analysis of technological innovation investments using fuzzy sets. *Technological and Economic Development of Economy*, *22*(2), 1-19. doi:10.3846/20294913.2014.994191

Sulaiman, I., Seheult, J., MacHale, E., D’Arcy, S., Boland, F., McCrory, K., … Costello, R. W. (2016). Irregular and ineffective: A quantitative observational study of the time and technique of inhaler use. *Journal of Allergy and Clinical Immunology: In Practice*, *4,* 900-909. doi:10.1016/j.jaip.2016.07.009

Tavassoli, S. (2015). Innovation determinants over industry life cycle. *Technological Forecasting and Social Change*, *91,* 18-32. doi:10.1016/j.techfore.2013.12.027

Taylor, M., & Taylor, A. (2012). The technology life cycle: Conceptualization and managerial implications. *International Journal of Production Economics*, *140,* 541-553. doi:10.1016/j.ijpe.2012.07.006

Teece, D., & Linden, G. (2017). Business models, value capture, and the digital enterprise. *Journal of Organization Design*, *6*(1), 1-14. doi:10.1186/s41469-017-0018-x

Thompson, C. G., Kim, R. S., Aloe, A. M., & Becker, B. J. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic and Applied Social Psychology*, *39*, 81-90. doi:10.1080/01973533.2016.1277529

Tidd, J., & Thuriaux-Alemán, B. (2016). Innovation management practices: Cross-sectorial adoption, variation, and effectiveness. *R&D Management*, *46*, 1024-1043. doi:10.1111/radm.12199

United Nations, Department of Economic and Social Affairs, Population Division. (2019). *World urbanization prospects: The 2018 revision (ST/ESA/SER.A/420)*. New York, NY: United Nations.

Utterback, J. M. (1996). *Mastering the dynamics of innovation*. Boston, MA: Harvard Business Press.

Velu, C. (2015). Business model innovation and third-party alliance on the survival of new firms. *Technovation*, *35*(Supplement C), 1-11. doi:10.1016/j.technovation.2014.09.007

Wang, Y., Pei, L., & Wang, Z. (2017). The NLS-based Grey Bass model for simulating new product diffusion. *International Journal of Market Research*, *59*(5), 655-669. doi:10.2501/IJMR-2017-045

Weeks, M. R. (2015). Is disruption theory wearing new clothes or just naked? Analyzing recent critiques of disruptive innovation theory. *Innovation: Management, Policy & Practice*, *17*, 417-428. doi:10.1080/14479338.2015.1061896

West, B. J. (2015). Exact solution to fractional logistic equation. *Physica A: Statistical Mechanics and Its Applications, 429*, 103-108. doi:10.1016/j.physa.2015.02.073

Woodside, A. G., Bernal, P. M., & Coduras, A. (2016). The general theory of culture, entrepreneurship, innovation, and quality-of-life: Comparing nurturing versus thwarting enterprise start-ups in BRIC, Denmark, Germany, and the United States. *Industrial Marketing Management*, *53*, 136-159. doi:10.1016/j.indmarman.2015.11.0030019-8501

Zacher, H., Robinson, A. J., & Rosing, K. (2016). Ambidextrous leadership and employees' self-reported innovative performance: The role of exploration and exploitation behaviors. *Journal of Creative Behavior*, *50*, 24-46. doi:10.1002/jocb.66

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Appendix B: SPSS Output for Overall Growth

```
LOGISTIC REGRESSION VARIABLES Growth
 /METHOD=ENTER Maturity Culture Company_Size
 /CONTRAST (Maturity)=Indicator
 /CONTRAST (Culture)=Indicator
 /CONTRAST (Company_Size)=Indicator
 /PRINT=GOODFIT CI(95)
 /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```

Logistic Regression

Notes

Output Created		09-MAY-2020 15:32:24
Comments		
Input	Data	H:\My Documents\Walden University\Working documents - Doc study\MyDR submissions\Yellow Tables\Dataset 50 samples 05-9-2020.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	50
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing

Syntax		LOGISTIC REGRESSION VARIABLES Growth /METHOD=ENTER Maturity Culture Company_Size /CONTRAST (Maturity)=Indicator /CONTRAST (Culture)=Indicator /CONTRAST (Company_Size)=Indicator /PRINT=GOODFIT CI(95) /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.04

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	50	100.0
	Missing Cases	0	.0
	Total	50	100.0
Unselected Cases		0	.0
Total		50	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Low Growth	0
High Growth	1

Categorical Variables Codings

		Frequency	Parameter coding (1)	(2)	(3)	(4)
Culture	North America	8	1.000	.000	.000	.000
	Europe	15	.000	1.000	.000	.000
	China	8	.000	.000	1.000	.000
	Japan	13	.000	.000	.000	1.000
	ROW	6	.000	.000	.000	.000
Company_Size	Small	22	1.000	.000		
	Midsize	14	.000	1.000		
	Large	14	.000	.000		
Maturity	Emergent	15	1.000	.000		
	Developing	19	.000	1.000		
	Mature	16	.000	.000		

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted Growth: Low Growth	High Growth	Percentage Correct
Step 0	Growth	Low Growth	43	0	100.0
		High Growth	7	0	.0
	Overall Percentage				86.0

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.815	.408	19.838	1	.000	.163

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Maturity	.669	2	.716
		Maturity(1)	.641	1	.423
		Maturity(2)	.307	1	.579
		Culture	5.442	4	.245
		Culture(1)	1.550	1	.213
		Culture(2)	.008	1	.929
		Culture(3)	4.368	1	.037
		Culture(4)	.581	1	.446
		Company_Size	1.191	2	.551
		Company_Size(1)	.004	1	.948
		Company_Size(2)	.891	1	.345
	Overall Statistics		7.547	8	.479

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	8.838	8	.356
	Block	8.838	8	.356
	Model	8.838	8	.356

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	31.659[a]	.162	.292

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1.510	8	.993

Contingency Table for Hosmer and Lemeshow Test

		Growth = Low Growth		Growth = High Growth		
		Observed	Expected	Observed	Expected	Total
Step 1	1	5	5.000	0	.000	5
	2	5	4.975	0	.025	5
	3	4	3.904	0	.096	4
	4	5	4.805	0	.195	5
	5	6	5.522	0	.478	6
	6	4	4.441	1	.559	5
	7	5	5.162	1	.838	6
	8	3	3.100	1	.900	4
	9	3	3.398	2	1.602	5
	10	3	2.692	2	2.308	5

Classification Table[a]

			Predicted		
			Growth		Percentage
	Observed		Low Growth	High Growth	Correct
Step 1	Growth	Low Growth	42	1	97.7
		High Growth	7	0	.0
	Overall Percentage				84.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Maturity			.973	2	.615	
	Maturity(1)	-1.209	1.801	.451	1	.502	.298
	Maturity(2)	-1.502	1.525	.971	1	.324	.223
	Culture			3.441	4	.487	
	Culture(1)	-20.721	13081.065	.000	1	.999	.000
	Culture(2)	-1.568	2.042	.589	1	.443	.209
	Culture(3)	1.402	1.411	.987	1	.321	4.062
	Culture(4)	-1.238	1.756	.497	1	.481	.290
	Company_Size			2.108	2	.349	
	Company_Size(1)	.777	1.364	.324	1	.569	2.175
	Company_Size(2)	2.093	1.555	1.813	1	.178	8.113
	Constant	-1.308	2.374	.304	1	.582	.270

Variables in the Equation

		95% C.I.for EXP(B)	
		Lower	Upper
Step 1[a]	Maturity		
	Maturity(1)	.009	10.179
	Maturity(2)	.011	4.420
	Culture		
	Culture(1)	.000	.
	Culture(2)	.004	11.416
	Culture(3)	.256	64.515
	Culture(4)	.009	9.061
	Company_Size		
	Company_Size(1)	.150	31.530
	Company_Size(2)	.385	170.807
	Constant		

a. Variable(s) entered on step 1: Maturity, Culture, Company_Size.