A CRITICAL ASSESSMENT OF CEO SUCCESSION ON ORGANIZATIONAL PERFORMANCE THROUGH DESCRIPTIVE AND PREDICTIVE RESEARCH METHODS

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Abstract: This research offers a comprehensive analysis of extant CEO succession literature to discover and illuminate previously unanalyzed variable relationships and potential areas for future research. An analysis is performed using both traditional regression-based statistical methods (descriptive) and machine learning methods (predictive) to compare the capabilities of the methodological approaches in analyzing complex relationships among the many variables in the underlying domain, ultimately demonstrating that the type of analytical lens used influences research outcomes. Results indicate that lead time is shown to be the greatest predictor of future firm financial performance following a change of CEO. The level of education of both the incumbent and incoming CEOs is shown to be virtually irrelevant to a company's financial performance when also factoring in several other relevant predictors. The downgrading of stocks by investment analysts is found not to impact firm performance. Previous CEO experience is determined not to be indicative of future company performance. Outgoing CEO age is demonstrated to be significantly positively related to future long-term firm financial performance. This research is the first to explore CEO succession and the impact of CEOs on firm financial performance using a machine learning methodology, providing methodological and theoretical contributions that should be considered by practitioners and researchers to advance research in these areas further.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

CHAPTER I

INTRODUCTION

Overview

Every organization struggles with the challenge of change. In the decades that researchers have investigated the impact of the demographics of Chief Executive Officers (CEO) and the characteristics of organizations, significant insights have been uncovered and put into practice, benefitting organizations of all sizes. However, despite the incremental advances achieved study after study, these insights and areas of research largely remain siloed and reflective of the past. In his renowned commencement address at Stanford University, Steve Jobs said, “you can’t connect the dots looking forward; you can only connect them looking backward. So, you have to trust that the dots will somehow connect in your future” (Jobs, 2005). This research serves to connect the dots of the past by unifying prior research, thereby allowing organizations to more effectively plan for the future.

CEOs are responsible for leading organizations and are therefore held accountable for both the successes and failures of organizations (Berns & Klarner, 2017; Quigley, Crossland, & Campbell, 2017). While much has been investigated regarding CEO succession (the transition from one leader to the next), as well as the indicators of the necessity of CEO succession (Cragun, Nyberg, & Wright, 2016; Zhu & Shen, 2016), many organizations continue to struggle with knowing exactly when a succession should occur (Harvey & Evans, 1994; Quigley et al., 2017), leaving organizations of all sizes and maturities with an imperfect and an incomplete understanding of a true roadmap to sustainable and optimal leadership (Berns & Klarner, 2017). In response to a call from Cragun, Nyberg, and Wright (2016) to improve the understanding of CEO succession *predictors* (indicators of an impending succession), this study presents a holistic analysis of multiple streams of CEO succession research to better understand the interactions among previously separately analyzed predictors. In addition to performing a holistic analysis of previous research through testing a fully integrated model, this dissertation exploring extant research with previously unanalyzed data using a novel machine learning approach (Mitchell, 1997) defines *machine learning* as the use of computer algorithms that improve automatically through experience).

Indeed, understanding the predictors of CEO succession is undoubtedly critical to the overall success of an organization (Davidson III, Nemec, & Worrell, 2001). However, organizations and CEOs seem to have a disproportionately difficult time looking in the mirror regarding the role of the CEO, which is to say that a need to change is more readily applied to other executive positions than to the CEO position. Indicative of this is research from McKinsey that shows that some 27 to 46 percent of executive transitions are acknowledged as failures within two years (Keller & Meaney, 2018). Furthermore, while many transitions are so-called failures, and 67 percent of leaders report that their organizations experience more transitions than before, the CEO turnover rate was only 16.6 percent in 2015 (Keller & Meaney, 2018). Whereas boards of directors and executives seek ever-improving firm financial performance, while often concurrently identifying and developing future organizational leadership, the subject of replacing the current CEO is often overlooked except in cases of significant missteps by the CEO, which lack of foresight comes at a significant cost (Rivolta, 2018). The potential cost of a CEO who remains in a position beyond an ideal time is either the resultant decreased firm performance or foregone or delayed increase in firm performance. Machine learning can play a critical role in understanding an organization's need to replace an incumbent CEO. It is the enhanced foresight resultant of predictor comprehension that will potentially improve the ability of organizations to improve the lead time of replacing a CEO (lead time is defined by Rivolta (2018) as the time from an announcement of a coming change of CEO to the time when the actual change takes place).

Lead time operates as the most important independent variable in this current study due to previous research (Rivolta, 2018) showing that a firm's performance following a succession event is most benefited by a longer lead time preceding the succession event. Figure 1 illustrates the observed lead times of the sample of this study. In Chapter II, a model (Figure 6) is proposed to holistically evaluate succession predictors and their impact on succession lead time and, ultimately, firm performance.

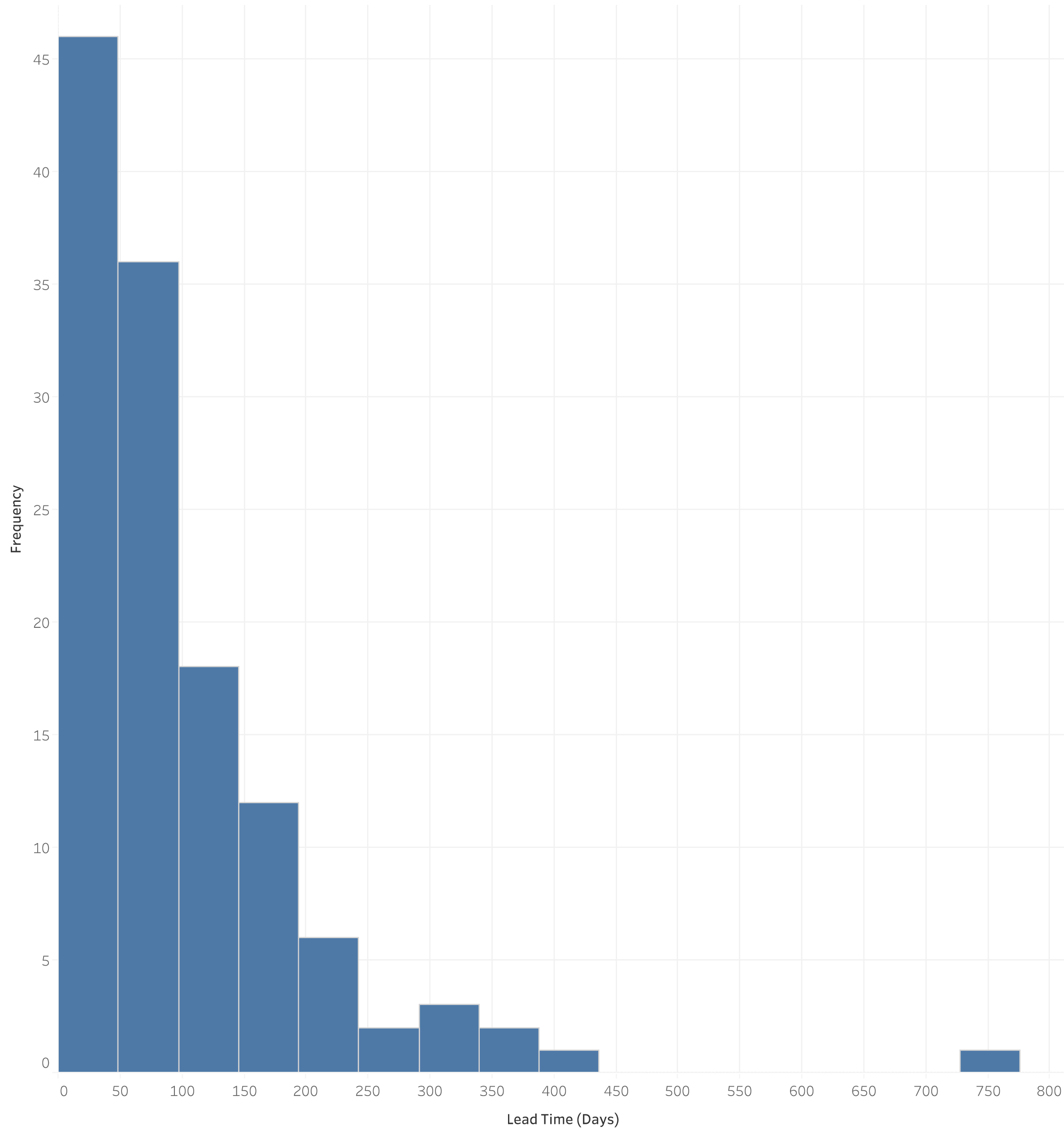

Figure 1. Lead Time

Statement of Purpose

The purpose of this research is to achieve a better understanding of the characteristics that influence CEO successions, as well as the relationship of lead time to such succession events, utilizing both traditional and machine learning methods. Analysis of multiple streams of CEO succession research contributes a more accurate representation of CEO succession predictors, further informing future research. Indeed, the decision of when to change the CEO of an organization can become more lucid with a better understanding of the many circumstances influencing such a decision (Bettis-Outland, 2012; Cragun et al., 2016). The improvement in performance resulting from increased knowledge of CEO succession predictors conceivably minimizes organizational costs while increasing the likelihood of achieving a successful CEO transition.

Problem Statement and Research Questions

In the United States, the primary decision-making bodies participating in governing the CEO position are traditionally the board of directors and the CEO (Cragun et al., 2016; Guthrie & Datta, 1997; Zhu & Shen, 2016). CEO succession research generally refers to variables or indicators that precede a succession "event" as predictors, which predictors ultimately culminate in the planning and execution of a change of CEO. The general problem is a lack of holistic understanding of CEO succession, impacting a firm's ability to plan and prepare for CEO turnover effectively and adequately. Rivolta (2018) identified significant costs to organizations' poorly planned or unexpected CEO departures. Harvey and Evans (1994) discuss the negative influence that suboptimal CEO departure lead time can have on successor development. If CEO succession lead time continues to be reactive, resulting from either a change in the incumbent CEO's plans or a board's decision to initiate a change due to poor performance (Cragun et al., 2016), organizations will continue to suffer significant losses due to poorly planned and executed CEO successions. As Figure 2 shows, over a third of firms experience negative free cash flow growth in the years following succession (34.6% negative growth; 65.4% positive growth).

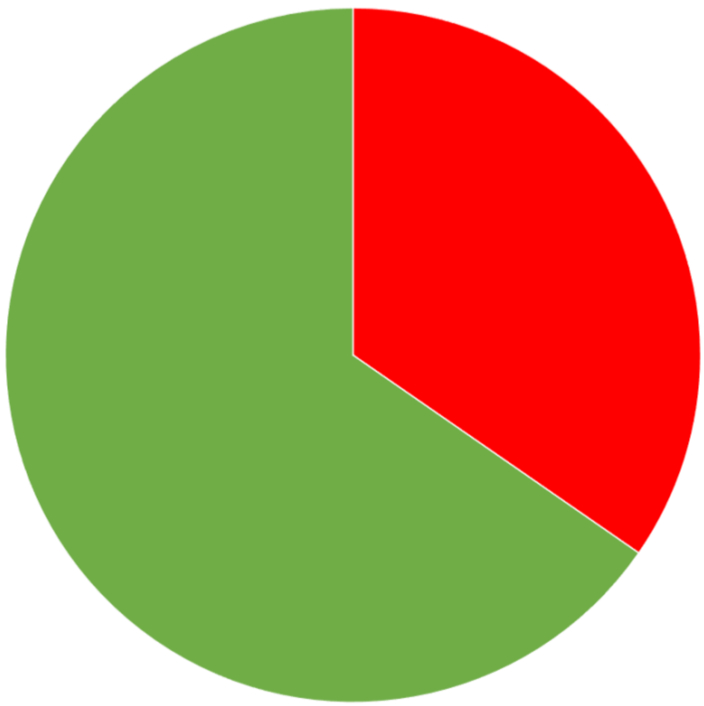

Figure 2. Post-Succession Firm Free Cash Flow Growth.

To substantially improve the ability of decision-makers to plan effectively and minimize the negative impact of change on an organization resulting from a CEO change, this research addresses one of the most critical problems faced by executives and boards of directors at companies of all sizes operating around the world:

Which CEO succession predictors most impact firm performance?

Based on personal, professional experience, extensive reviews of previous research, and diagnosis of the research problem, the questions this study investigates are:

1) Does the lead time of a CEO succession event significantly influence the financial performance of a firm?
2) Does the lead time of a CEO succession event mediate the impact of a succession event on firm financial performance?
3) Of the known CEO succession predictors, which are most significant when considered concurrently?
4) Are CEO succession predictors more accurately analyzed by machine learning than by traditional linear regression?

Contributions of the Study

There are four primary contributions of this research. First, this analysis builds on prior research relating to CEO succession (Berns & Klarner, 2017; Cragun et al., 2016) by evaluating many oft-researched predictors simultaneously, allowing for a more complete, comprehensive, and holistic perspective of CEO succession predictors. Second, machine learning is introduced as a novel and effective methodological instrument to assess and determine the need of an organization to initiate a change of CEO.

Third, governance, strategy, and machine learning literature are enriched. This current study brings together multiple streams of research while allowing machine learning algorithms to effectively and unbiasedly evaluate and rank previously validated indicators of CEO succession.

Finally, this research provides pragmatic insights that CEOs, executives, and board of directors can use to plan for succession events more effectively. While this research adds to the understanding of the succession process, organizational leaders will be able to plan for future CEO succession without compromising firm performance or having complete candor impeded by awkward or uncomfortable feelings surrounding the incumbent CEO.

This dissertation not only brings together fragmented extant research, but is novel in the application of predictive analytics, machine learning in particular, to CEO succession events, thereby providing boards of directors, CEOs, and other stakeholders with a more complete and lucid understanding of their circumstances and opportunities for change and improvement.

Organization of the Study

The remainder of the study is presented as follows: Chapter II presents a review of the literature, providing an in-depth analysis of previous research, key constructs, machine learning as a contribution to literature, hypothesis development, and the presentation of the theoretical model. Chapter III presents the methodologies and measures used in this study, along with a description of the data, items, and measures. It also explains the software and techniques used in the study. Chapter IV details the results, reliability and correlation analysis, regression modeling, machine learning modeling, comparison of methodological approaches and outcomes, overall model fit, and hypothesis testing. Chapter V discusses theoretical and practical implications, research limitations, future research, and conclusions.

CHAPTER II

REVIEW OF LITERATURE

Succession challenges confront organizations of all sizes and stages. Boards of directors of large public corporations balance public perception, internal politics, and strategic plans when considering the replacement of a Chief Executive Officer (Bosse & Phillips, 2016). Furthermore, founding CEOs inevitably face the difficult decision of relinquishing the CEO role of the organization they themselves built to a more experienced and traditional CEO who is better suited to guide the venture as it transitions through the growth stage to maturity (Fischer & Pollock, 2004).

This chapter begins as a review of the research of CEO succession, effectively laying the foundation for the development and presentation of the hypotheses and model to be explored further. Whereas multiple regression is the predominant method of analysis of CEO succession, it is only presented in Chapter III. Therefore, an overview of machine learning is presented here in Chapter II to introduce how a contemporary methodology can enhance succession research.

Background of CEO Succession Research

CEO succession research has yielded many valuable and diverse insights regarding how CEO succession occurs, the influence and role of a CEO in the organization and succession process, and how boards and CEOs determine the need for succession. The following section is a review of relevant succession research.

CEO Succession and Agency Theory

Many variables have been studied relative to CEO succession. The literature often cites agency theory, suggesting that while CEOs are responsible for acting for the company's benefit, however, CEOs also have personal characteristics and propensities that may at times come in conflict with firm performance. CEO succession literature and agency theory combine to address most of the predictors referenced by Berns and Klarner (2017).

Matta and Beamish (2008) discovered through a sample of 293 international acquisitions that CEOs nearing retirement are generally more risk-averse than those with a longer horizon towards retirement, or that those with more to lose (in the form of in-the-money unexercised options) are less likely to engage in risk-taking firm behavior. This suggests the influence that CEOs may have on a company's performance as a change of CEO is being considered, either actively or simply within the CEO alone. While age is not an indicator of nearness to retirement, Figure 3 illustrates the ages of the old, or incumbent, CEOs juxtaposed with the ages of the new incoming CEOs in the sample of firms in this study.

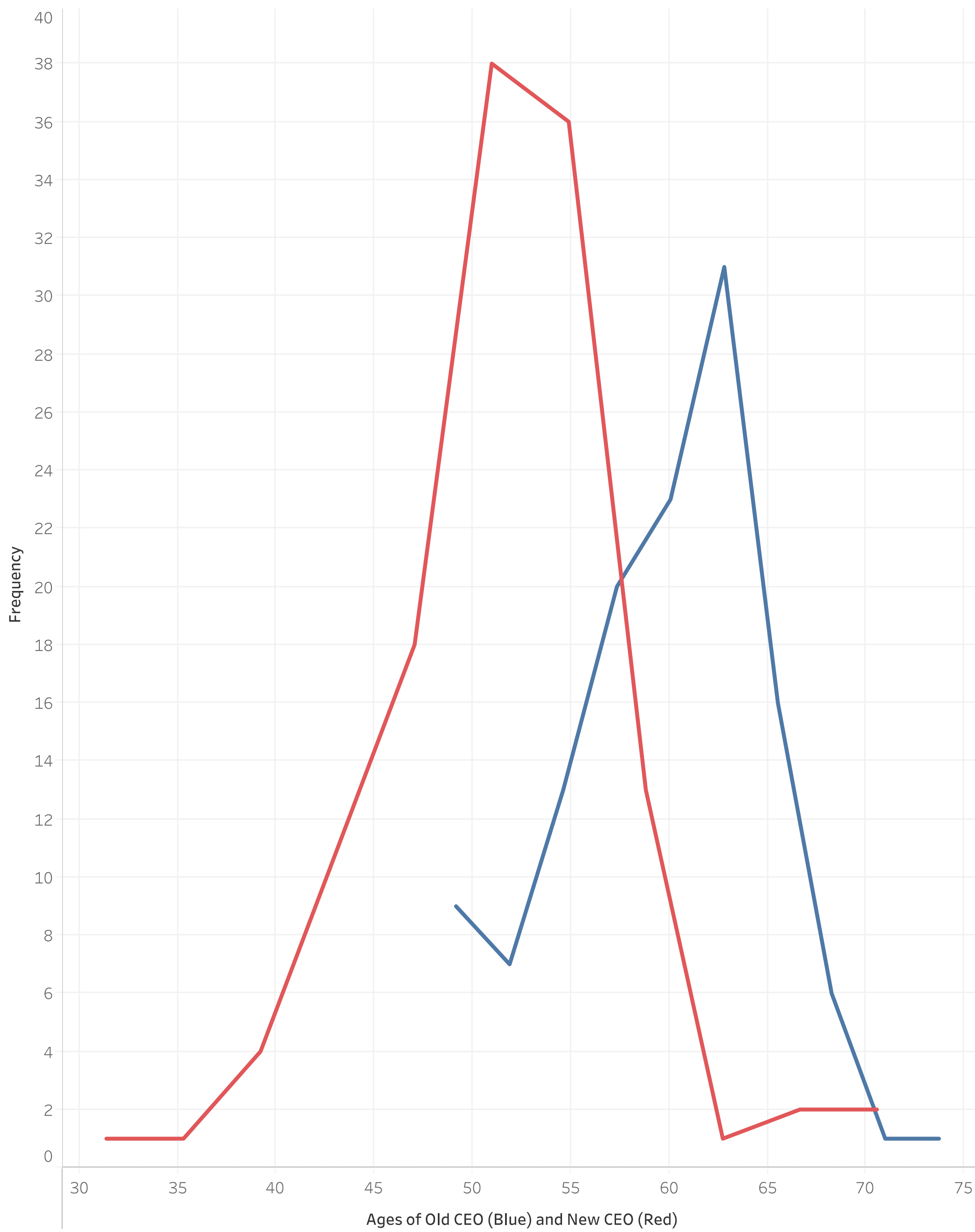

Figure 3. Old and New CEO Ages

Figure 4 extends the understanding of the circumstance of the incumbent CEOs by illustrating the tenures of incumbent CEOs in their positions.

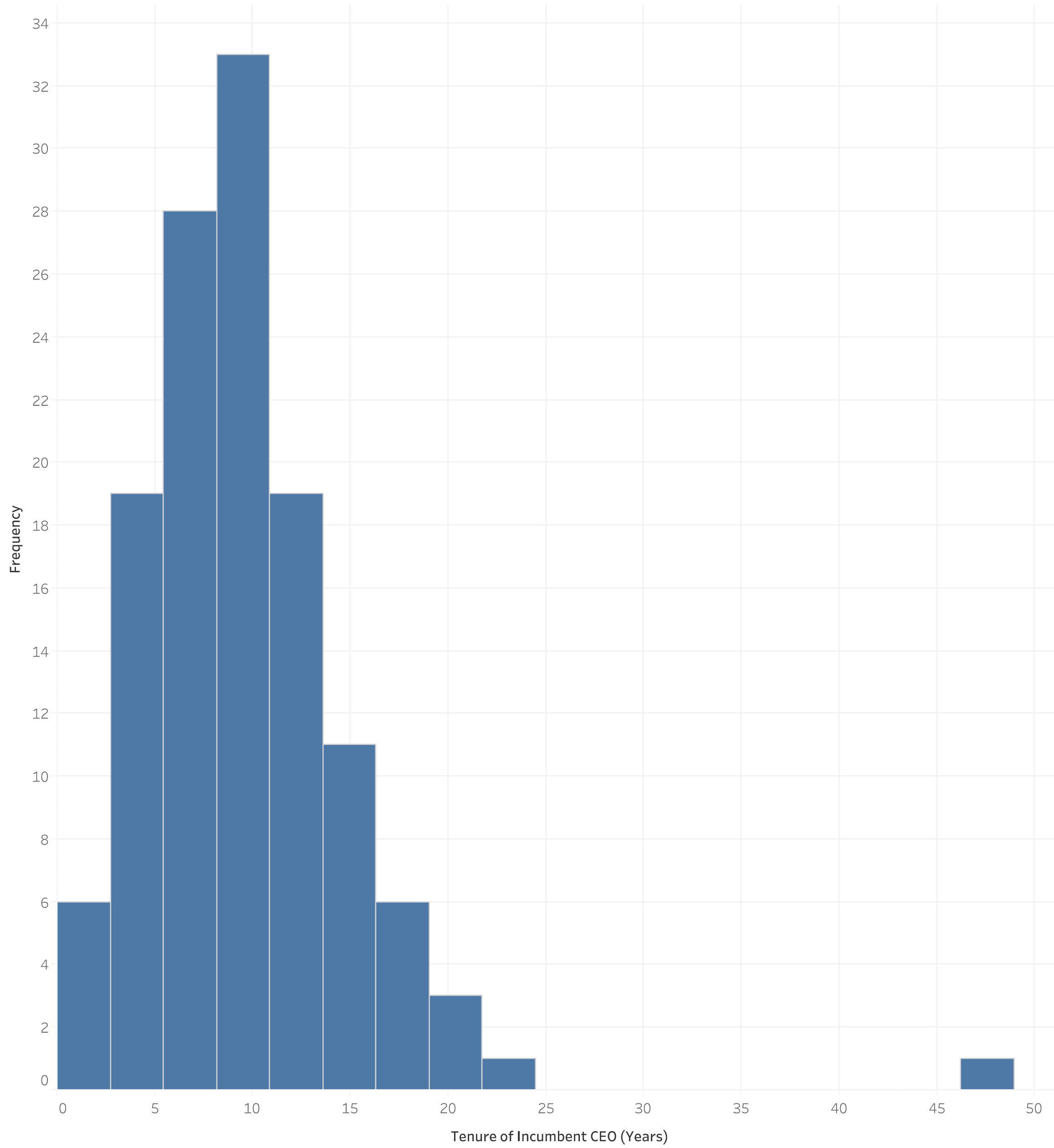

Figure 4. Tenure of Incumbent CEO

Berns and Klarner (2017) conducted a comprehensive analysis of CEO succession literature, suggesting that succession events would be better categorized and studied as processes wherein the incumbent CEO may have friction with the board of directors at various points in the succession process. It is conceivable that improved lead time of succession events may reduce friction points between the CEO and the board of directors, the CEO and the incoming CEO, and the CEO and the organization.

Cragun et al. (2016) conducted a comprehensive analysis of various CEO succession literature. This paper highlights a critical shortcoming in CEO succession literature that this dissertation seeks to overcome: “the best we can do” right now is to review past successions. This reactive approach leaves organizations exposed to poorly timed successions. This current study aims to minimize the adverse effects of the succession event by clarifying the best way for succession to occur, given the characteristics that exist. Walther, Morner, and Calabró (2015) further explore the consequences of decisions made throughout the CEO succession process, including at the critical initialization stage where the need for a change of CEO is determined.

Fischer and Pollock (2004) evaluated 218 initial public offering (IPO) deals from 1992, finding that a founding CEO’s presence, as well as the average management team’s tenure, at the time of a significant transformational event decreased the likelihood of failure. The calming effect of a longer-tenured management team suggests that if an organization had a longer horizon to CEO change, the new CEO could begin sooner to become prepared and familiarized with the organization to reduce the likelihood of failure.

Schepker, Nyberg, Ulrich, and Wright (2018) explored succession planning processes, discovering that boards’ use of formal succession processes and access to information results in a positive outcome of succession planning, suggesting that additional data provided by machine learning analysis of the organization and CEO could further improve succession outcomes. Furthermore, the study did not find statistically significant support of CEO influence on succession outcomes, suggesting that the "elephant in the room" that boards struggle with confronting may not be a serious threat to organizations as they attempt to plan for future leadership changes. Of this, Schepker and colleagues note that past CEO research is anchored in agency theory, with CEO behavior being opportunistic and self-serving. It is, therefore, possible that CEOs may utilize their influence in positive ways more so than previous research has intimated. It is also worth considering the invitation of Schepker et al. that agency theory may not be the preferred theory to anchor CEO succession research.

In a comprehensive review of the literature at the time, Eisenhardt (1989) suggested that an agency perspective be incorporated in research problems involving a cooperative structure, such as this. This current study explores agency theory to acknowledge the prevalence of the theory in CEO succession literature, as well as to highlight the conflicting perspectives that have become intertwined within CEO research, in hopes that a change in methodological approach may contribute to the clarification of CEO and CEO succession literature.

Regarding agency theory, Bosse and Phillips (2016) note that CEO self-interest can be mitigated through reciprocity with the board, initiating positive reciprocity. This may be achieved through improved communication resultant of the data that could be generated from this current research to inform and improve the lead time of CEO succession events. Furthermore, Pugliese, Minichilli, and Zattoni (2014) suggest that a form of this reciprocity (board monitoring of CEO and CEO performing advice tasks) is negatively associated with firm performance, or rather, that as a firm performs well, a board is less inclined to monitor or take umbrage with a CEO's performance, while in turn, a CEO is less likely to take direction from a board.

Chari, David, Duru, and Zhao (2019) take an agency theory approach to evaluating the concerns that shareholders have regarding risk-averse managers, such as CEOs approaching retirement. Chari and colleagues recommend improved alignment of managers with shareholders and the board, which Schepker et al. (2018) suggested may come from additional information and data.

Davidson III et al. (2001), in continuation of Davidson, Worrell, and Nemec's (1998) research of agency theory and plurality, produced findings that run contrary to agency theory, suggesting that the incumbent CEO does not negatively influence succession outcomes so long as the heir apparent is identified. If organizations could know with greater confidence that CEO succession is needed at some point in the future, succession planning could be improved, and adverse outcomes would be minimized. Harris and Helfat (1998) point out that plurality may inhibit the board's ability to properly plan and prepare for future executive leadership change, albeit while supporting the agency problem presented by the current CEO.

Masulis, Wang, and Xie (2009) support agency theory, finding that managers and CEOs with access to extractable internal value make shareholder value-destroying acquisitions more frequently and that capital expenditures contribute less to shareholder value. Agency problems such as this contribute to the need for CEO succession, as a CEO's control may contribute to decreasing shareholder performance.

Nyberg, Fulmer, Gerhart, and Carpenter (2010) support agency theory, finding that alignment between CEO and shareholder interests significantly impacts firm performance. Thus, if organizations could better identify when a CEO will no longer be in alignment with shareholder interests, succession could help to avoid shareholder losses.

Stroh, Brett, Baumann, and Reilly (1996) support and refute agency theory, highlighting the diverging backing of the key theory of the CEO role and succession. Specifically, the authors found that managers prefer to remain with an organization longer and exhibit fewer agency problems when compensation includes less variable pay.

Of note in discussing agency theory is stewardship theory (Davis, Schoorman, & Donaldson, 1997). Stewardship theory stands in contrast to agency theory (Eisenhardt, 1989). Whereas agency theory argues that an individual should and is naturally predisposed to make decisions and act in a way that is self-benefiting (if all individuals within an organization act in their own best interest, the organization will ultimately benefit — "what's good for the goose is good for the gander"), stewardship alternatively argues that if a steward leader is empowered, he or she will perform so as to most benefit the organization, thereby optimizing the net benefit to the organization (Davis et al., 1997). Stewardship theory posits that managers, on their own, act as responsible stewards of the assets they control and assumes that given a choice between the self-serving behavior of an agent and pro-organizational behavior of a steward, a steward will place a higher value on the potential impact of their responsibility on an organization.

Given the responsibility of organizational leadership and board of directors to act as stewards of the organization (Davis et al., 1997), responsibly acting for the benefit of their organization, a misalignment in CEO and board or CEO and organization objectives could create friction points in an organization's implementation of strategy or otherwise typical management.

Board independence has been referenced as a possible mitigator of the costs of agency behavior, or as a way of ensuring stewardship behavior, despite the conclusions of meta-analyses of the impact of board composition on a company's performance finding that board independence does not consistently improve firm performance (Dalton, Daily, Ellstrand, & Johnson, 1998; Dalton & Dalton, 2011).

CEO Succession Research Methodology Summary

Previous research has used traditional, regression-based methodologies. While this has improved our knowledge base about CEO succession events, they have been splintered and not very utilitarian for organizations. This section reviews prior research methods to justify the concept of machine learning as a way to expand understanding and utility of CEO succession research.

To demonstrate the lack of utilization of machine learning techniques, Table 1 presents a summary of primary research methods in CEO succession research.

Table 1. CEO Succession Research Primary Research Methods

STUDY	PRIMARY METHOD
Agrawal, Knoeber, & Tsoulouhas (2006)	Traditional Quantitative Method
Ballinger & Marcel (2010)	Traditional Quantitative Method
Baran & Forst (2015)	Traditional Quantitative Method
Barron, Chulkov, & Waddell (2011)	Traditional Quantitative Method
Beatty & Zajac (1987)	Traditional Quantitative Method
Bernard, Godard, & Zouaoui (2018)	Traditional Quantitative Method
Boeker (1992)	Traditional Mixed Method
Boeker & Goodstein (1993)	Traditional Quantitative Method
Borokhovich, Parrino, & Trapani (1996)	Traditional Quantitative Method
Bragaw & Misangyi (2017)	Traditional Quantitative Method
Cannella & Lubatkin (1993)	Traditional Quantitative Method
Cannella & Shen (2001)	Traditional Quantitative Method
Cao, Maruping, & Takeuchi (2006)	Conceptual
Chen & Hambrick (2012)	Traditional Quantitative Method
Chen, Luo, Tang, & Tong (2015)	Traditional Quantitative Method
Chung & Luo (2013)	Traditional Quantitative Method
Chung et al. (1987)	Traditional Quantitative Method
Connelly, Ketchen, Gangloff et al. (2016)	Traditional Mixed Method
Dalton & Kesner (1985)	Traditional Quantitative Method
Datta & Guthrie (1994)	Traditional Quantitative Method
Datta, Rajagopalan, & Zhang (2003)	Traditional Quantitative Method
Davidson, Worrell, & Dutia (1993)	Traditional Quantitative Method
Davidson III, Nemec, & Worrell (2001)	Traditional Quantitative Method
Elsaid, Wang, & Davidson III (2011)	Traditional Quantitative Method
Fischer & Pollock (2004)	Traditional Quantitative Method
Friedman & Olk (1995)	Conceptual
Friedman & Saul (1991)	Traditional Mixed Method
Friedman & Singh (1989)	Traditional Mixed Method
Georgakakis & Ruigrok (2017)	Traditional Quantitative Method
Graffin, Boivie, & Carpenter (2013)	Traditional Quantitative Method
Grusky (1960, 1961)	Traditional Quantitative Method
Guthrie & Datta (1997)	Traditional Quantitative Method
Hamori & Koyuncu (2015)	Traditional Quantitative Method
Harvey & Evans (1994)	Conceptual
Helmich & Brown (1972)	Traditional Quantitative Method
Herrmann & Datta (2002)	Traditional Quantitative Method
Ishak, Ismail, & Abdullah (2012)	Traditional Quantitative Method
Jalal & Prezas (2012)	Traditional Quantitative Method

STUDY	PRIMARY METHOD
Karaevli (2007)	Traditional Quantitative Method
Karaevli & Zajac (2013)	Traditional Quantitative Method
Lauterbach, Vu, & Weisberg (1999)	Traditional Quantitative Method
Magnusson & Boggs (2006)	Traditional Quantitative Method
Matta & Beamish (2008)	Traditional Quantitative Method
Mooney, Semadeni, & Kesner (2017)	Traditional Quantitative Method
Naveen (2006)	Traditional Quantitative Method
Ocasio (1994)	Traditional Quantitative Method
Palomino & Peyrache (2013)	Traditional Quantitative Method
Parrino (1997)	Traditional Quantitative Method
Quigley & Hambrick (2012)	Traditional Quantitative Method
Quigley, Crossland, & Campbell (2017)	Traditional Quantitative Method
Rivolta (2018)	Traditional Quantitative Method
Sardeshmukh & Corbett (2011)	Traditional Quantitative Method
Schepker, Nyberg, Ulrich, & Wright (2018)	Traditional Quantitative Method
Schwartz & Menon (1985)	Traditional Quantitative Method
Shen & Cannella (2002a, 2002b, 2003)	Traditional Quantitative Method
Tian, Haleblian, & Rajagopalan (2011)	Traditional Quantitative Method
Tushman & Rosenkopf (1996)	Traditional Quantitative Method
Virany, Tushman, & Romanelli (1992)	Traditional Quantitative Method
Walther, Morner, & Calabrò (2015)	Conceptual
Weng & Lin (2014)	Traditional Quantitative Method
Westphal & Fredrickson (2001)	Traditional Quantitative Method
Wiersema & Zhang (2011)	Traditional Quantitative Method
Worrell, Davidson, Chandy et al. (1986)	Traditional Quantitative Method
Zajac (1990)	Traditional Quantitative Method
Zajac & Westphal (1996)	Traditional Quantitative Method
Zhang (2006, 2008)	Traditional Quantitative Method
Zhang & Rajagopalan (2003, 2004, 2010)	Traditional Quantitative Method
Zhu & Shen (2016)	Traditional Quantitative Method

Grounding CEO Succession Research Problems and Questions

To restate the problem, analysis of organizations that fail to effectively make a change in the CEO position in a timely manner experience negative financial performance and reputational damage (Cragun et al., 2016). Understanding succession predictors has been evidenced in a range of industries through well-timed CEO changes, resulting in significant improvements in firm performance (Rivolta, 2018). Examples abound of companies whose successful CEO successions have led the firms to stock price increases above market averages (new CEO dates of examples presented in Table 2 below average 4/1/18, and market stock prices thru 7/30/19 experienced increases of 17.59% for Dow Jones Industrial Average and 24.40% for S&P 500 Index, for approximate comparison).

Table 2. New CEO Stock Performance

Company	New CEO Date	% Stock Gain thru 7/30/19
Ansys	1/1/17	175.34
Chipotle Mexican Grill	3/5/18	159.74
Lam Research	12/5/18	112.32
Starbucks	4/3/17	51.9
Tyson Foods	9/30/18	48.53
Intuit	1/1/19	40.85
Northrop Grumman	1/1/19	39.75
Xilinx	1/29/18	36.81
Hershey	3/1/17	35.85
Xerox	5/14/18	32.25
Equinix	9/12/18	29.98

Industries with high dynamism face the constant threat of irrelevance and loss of competitive positioning that results from hesitation in changing a CEO (Walther et al., 2015). Improved understanding of the predictors indicating the need for CEO change represents a critical step in maintaining and improving firm performance (Cragun et al., 2016). Therefore, reframing the understanding of the indicators for the necessity of CEO change is an essential and critical issue.

The challenge of improving CEO succession event lead time is exceedingly complex and is far too deep to perfectly and completely address in a single study. However, personal participation in and observation of many CEO succession events provides sufficient anecdotal support to the notion that the framework presented by Berns and Klarner (2017) as a comprehensive summary of current CEO succession research (see Figure 5) indicates a critical omission of lead time as an influential factor in CEO succession outcomes.

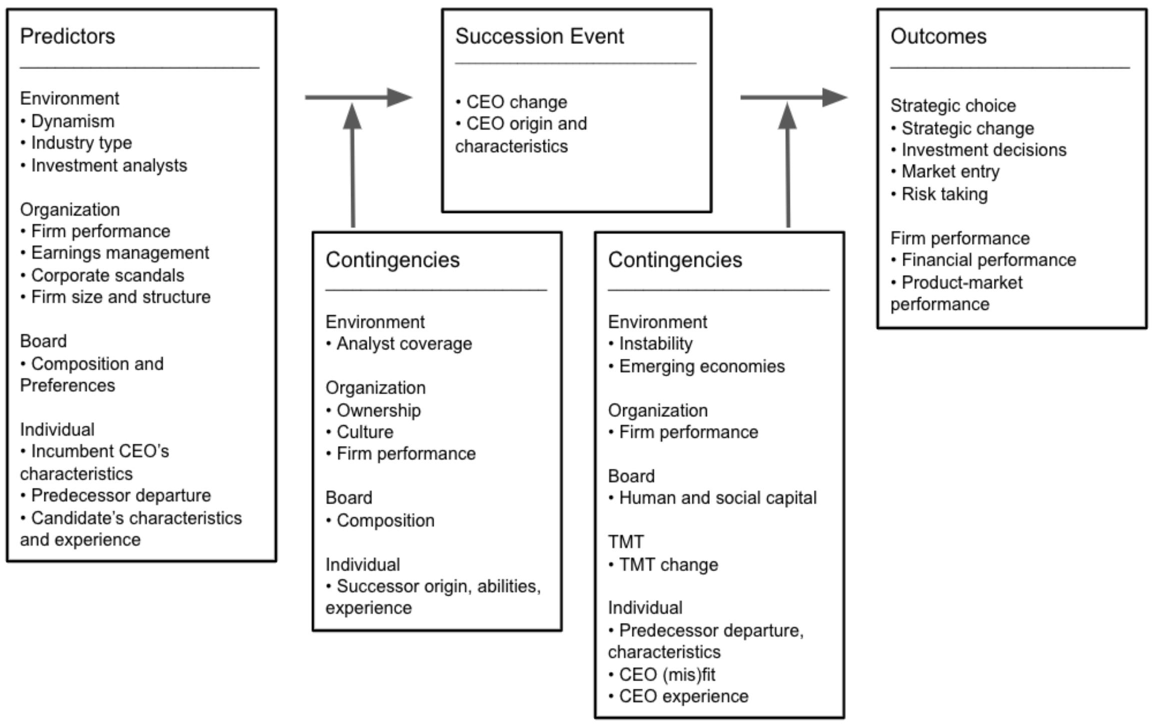

Figure 5. Berns and Klarner (2017) Proposed Framework of CEO Succession Research.

Background of Machine Learning in CEO and Succession Research

Researchers have called for increased utilization of big data methods and predictive analytics in the organizational sciences (Tonidandel, King, & Cortina, 2016). Given the vast amount of data available now and significant advances in predictive capacity, the scientific and practical application of predictive analytics in CEO succession brings a novel and a clear new perspective to the literature (Haig, 2020).

Machine Learning

Machine learning is a part of artificial intelligence that refers to the study of algorithms that improve automatically through experience (Mitchell, 1997). The models built by machine learning come from sample data, or "training data," with the purpose of making decisions or predictions despite not being programmed to do so (Koza, Bennett, Andre, & Keane, 1996). Within the business context, machine learning is often referred to as predictive analytics, wherein a business can analyze current and historical information to predict future events (Eckerson, 2007). Predictive models guide decision-making processes by exploiting patterns found in data (Coker, 2014), helping to consider large and diverse sets of information. With previous CEO succession research considering many different predictors (Berns & Klarner, 2017; Cragun et al., 2016), it is necessary to bring together and analyze a great deal of data to synthesize the findings accurately and adequately to predict the need for CEO succession (Chang, Kauffman, & Kwon, 2014).

In supporting the leveraging of big data in organizational research, McAbee, Landis, and Burke (2017) note that despite the clear need for increased accuracy in CEO succession necessity modeling, the current application of machine learning in the social sciences has been restricted to the areas of personality and social psychology, wherein available data is robust given the digital breadcrumbs that researchers have convenient access to (e.g., Kosinski, Bachrach, Kohli et al, 2014; Kosinski, Stillwell, & Graepel, 2013; Youyou, Kosinski, & Stillwell, 2015).

Chang et al. (2014) and Kauffman and colleagues (2017) suggest that interdisciplinary convergence (in this case, CEO succession research converges with machine learning as a new way of analyzing many predictors) generates new research questions and perspectives that can contribute to the existing bodies of literature of the converging disciplines.

Contrasting Methodological Role of Machine Learning

Although an explosion in available data and significant advances in predictive modeling methods exist (Putka, Beatty, & Reeder, 2017), organizational and social sciences have yet to fully embrace machine learning as a viable and robust analytical tool (Tonidandel et al., 2016). The ultimate objective of machine learning analysis is to explore sets of data to detect complex yet stable relationships among variables (Oswald, Behrend, Putka, & Sinar, 2019). Whereas succession and other strategic leadership research generally utilize traditional inferential statistics in analysis, this current study argues that a hypothetico-deductive hypothesis testing approach, while certainly playing a critical role in establishing theory, insufficiently explains all interactions between variables. In presenting an abductive theory of the scientific method, this current study proposes that this data-before-theory sequence of inquiry compliments traditional research with further validation of findings and explanatory goodness while also seeking to generate explanatory theories by methodological means (Haig, 2020).

Support for the application of machine learning in lieu of traditional inferential statistics (e.g., variance analysis or linear regression analysis) has been provided by many researchers (Breiman, 2001; Kuhn & Johnson, 2013; Shmueli, 2010), with the authors suggesting that the improved accuracy is resultant of more robust data sets, less statistical assumptions in analysis, more effective capturing of non-linear inter-variable relationships, and the automatic inclusion of interaction effects between variables (Müller, Junglas, vom Brocke, & Debortoli, 2016). This is not to say that traditional methods have diminished in value or are inherently inferior to newer methodological approaches such as machine learning. For this current study's purpose, both forms of analysis are performed to compare and contrast outcomes. As Wenzel and Van Quaquebeke (2018) point out, there are no perfect methods. All have some degree of limitations or assumptions that require a methodological approach to be determined based on the problem in question and available data.

Decision Tree Learning and Random Forest Techniques

Machine learning algorithms aim to build mathematical models based on sample data in order to make decisions, distill explanations, or generate predictions. In this research, machine learning is considered due to common consideration of the antecedents to CEO succession as "predictors," as well as the capacity of machine learning to support the decisions that organizations must make in the succession planning process.

There are many machine learning methods, many of which are used as "BlackBox" models, that offer very little explanation. In this current study, decision tree learning and random forest techniques are used because they are the most transparent and explainable, allowing for relationships and outcomes to be contextualized and supported by underlying theory. Decision tree learning is one of the most common methods in machine learning to solve regression and classification problems.

Overfitting due to decision tree application is mitigated by random forest, wherein multiple decision trees are combined and trained over randomly distributed training data, producing an improved classification outcome. In essence, random forest is implemented by creating multiple decision trees towards a target variable or attribute. Every branch point, or node, is, therefore, a condition or decision based on a single parameter, splitting the underlying data into two classifications. Random forest then uses regression, or mean prediction, of each individual tree, ultimately finding the subset of variables or features that best explain a given tree and the model as a whole while being robust to noise and outliers (Garcia, Nebot, & Vellido, 2017).

The random forest method has been used in previous business-related studies. For example, Whitrow, Hand, Juszczak, Weston, and Adams (2009) apply random forest to the detection of credit card fraud through analysis of approximately 47,000 observations. Furthermore, Whitrow et al. comparatively indicate that random forest returned classification results superior to other classification algorithms. In analyzing churn using random forest, Xie, Li, Ngai, and Ying (2009) apply random forest in concert with other techniques to predict customer churn in the banking industry. Buckinx (2005) analyzed defection of loyal, non-contract retail clients, Burez (2007) reduced customer attrition among TV customers, and Larivière (2005) predicted retention and profitability within a European financial services company.

Machine Learning Summary

Applying machine learning or predictive analytics to CEO succession planning problems remains a novel concept whose application is largely dependent on the industry in question. Despite the increasing popularity of random forests in the research areas of decision sciences and predictive analytics, the application of machine learning (in particular, random forest) in the organizational sciences such as succession research remains scarce at best. Whereas management and strategy literature has yet to embrace machine learning as a methodological analytic tool fully, industry thinkers have signaled a desire to leverage machine learning in improving succession planning through a better understanding of succession predictors. Even so, practitioner firms such as Oracle (Brockbank & Turi, 2018) and Ascendify (Hinman, 2018) limit the potential role of machine learning to identifying and preparing successors based on well-researched criteria such as ideal and optimal CEO characteristics, creating strategies to bridge skills and knowledge gaps, and other learning and development objectives. While the bleeding edge of pragmatic succession research remains focused on identifying successors, these researchers, nor academic researchers, have not critically considered the lead time of CEO succession events to be strategically critical. With approximately 10,000 people in the United States turning 65 every day (Staff, 2019), leaders are confronting the reality of the impending train wreck of massive managerial turnover without knowing how to identify the optimal timing of a change for specific individuals. This current research provides clarity for organizations by filling in the gaps with a clearer understanding of predictors and their relationships with other organizational and individual factors.

Hypothesis Development and Conceptual Models

Following is a presentation of key constructs, variables, and hypotheses tested in the form of traditional models through traditional linear regression, as well as through a contemporary machine learning research design.

Key Constructs and Variables

Previous research has identified several predictors of CEO succession, generally categorized at the board, environmental, individual (CEO), and organizational levels (Berns & Klarner, 2017). Table 3 presents a review of the most commonly considered predictors of CEO succession as found in literature, with the predicted relationship strength and direction regarding the variable's interaction with the dependent variable of firm financial performance, a key outcome of CEO succession (Berns & Klarner, 2017).

Table 3. Summary of Model Variables

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Lead Time	Number of days from the time of CEO departure announcement to the actual takeover date of new CEO.	Rivolta (2018)
Beta (Industry)	Average stock Beta across the industry for calendar year preceding succession event. Beta coefficient measures volatility of a stock compared to systematic market risk. Comparable to Rivolta's use of standard deviation of stock price during the prior calendar year.	Rivolta (2018)
Standard Deviation of Equity (Industry)	The standard deviation in weekly stock prices within the industry, estimated using two years of data. The number is annualized.	

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Standard Deviation of Operating Income (Industry)	This coefficient of variation is a measure of earnings volatility over the last 10 years in the firm's industry and is computed only for firms that have been in existence, and have data, for the last 10 years.	
Average Tax Rate (Industry)	This is the effective industry tax rate, obtained by dividing the taxes paid by the taxable income as reported to the stockholders. Marginal tax rates would be ideal, but these are not reported.	
Investment Analyst Downgrade	Downgrading of firm stock by analysts increases likelihood of CEO dismissal.	Wiersema & Zhang (2011)
Time from Downgrade to Announcement	Downgrading of firm stock by analysts increases likelihood of CEO dismissal.	Wiersema & Zhang (2011)
Pre-Succession ROA	Operating income to total assets as indicator of profitability of company relative to its total assets. Poor firm performance enhances likelihood of CEO succession. Calculated from one year prior to the departure of the incumbent CEO.	Hamori & Koyuncu (2015); Parrino (1997); Rivolta (2018)
Pre-Succession Income	Accounting measure of profit from business operations after operating expenses.	Rivolta (2018)
Natural Log of Assets	Natural log of book value of pre-succession assets as proxy for complexity of incumbent CEO's job.	Jalal & Prezas (2012)
Corporate Scandals	Binary variable (0, 1) indicates whether the incumbent CEO was found to engage in unethical or illegal activities while acting as CEO, as made known in public information.	Cao, Maruping, & Takeuchi (2006); Ertugrul & Krishnan (2011)

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Firm Size	Market capitalization at time of succession.	Berns & Klarner (2017); Finkelstein et al. (2009)
Firm Age	Age of the firm in years at the time of the succession event.	Rivolta (2018)
Time Without Leadership	Number of days a firm operates without CEO leadership.	Rivolta (2018)
Board Size	Number of people comprising the board of directors.	Schepker, Nyberg, Ulrich, & Wright (2018)
Board External Composition	Refers to the percentage of external/outside board members.	Berns & Klarner (2017); Rivolta (2018)
Board Executive Chairman or CEO	Indicates the presence of an executive chairman on the board of directors, or the CEO is the chairman.	Davidson III, Nemec, & Worrell (2001)
Incumbent CEO Age	Refers to the age of the incumbent CEO at time of succession event. Research has shown that CEOs of increasing age adopt less risky strategies.	Chowdhury & Fink (2017); Serfling (2014)
Incumbent CEO Tenure	Refers to the length of time the incumbent CEO has held the CEO position.	Guthrie & Datta (1997)
Incumbent CEO Undergraduate Degree	Binary variable (0, 1) indicating whether the incumbent CEO completed an undergraduate degree (1) or not (0). Research has shown that CEO education plays a role in the selection of a new CEO, yet does not influence the decision to replace a CEO, nor does it affect the firm performance in the long-term. However, other research has shown that CEO education results in more risky and innovative business models.	Bhagat, Bolton, & Subramanian (2010); King, Srivastav, & Williams (2016)

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Incumbent CEO Graduate Degree	Binary variable (0, 1) indicating whether the incumbent CEO completed a graduate degree (1) or not (0). Research has shown that CEO education plays a role in the selection of a new CEO, yet does not influence the decision to replace a CEO, nor does it affect the firm performance in the long-term. However, other research has shown that CEO education results in more risky and innovative business models.	Bhagat, Bolton, & Subramanian (2010); King, Srivastav, & Williams (2016)
Incumbent CEO Previous CEO Experience	Binary variable (0, 1) indicates whether the incumbent CEO had held at least one CEO position prior to current position (1) or not (0). Many studies have supported that a CEO's previous experience can influence market performance, firm financial performance, and even post-succession performance.	Bragaw & Misangyi (2017); Elsaid, Wang, & Davidson III (2011); Guthrie & Datta (1997); Hamori & Koyuncu (2015); Zhu & Shen (2016)
Unexpected CEO Unexpected Death or Illness	Binary variable (0, 1) indicates whether the incumbent CEO's departure was unexpected (1) or not (0).	Rivolta (2018)
Heir Apparent	Binary variable (0, 1) indicates whether a firm is identified as having an heir apparent (1) at time of succession or not (0), identified as such by virtue of a non-CEO executive, being at least five years younger than the incumbent CEO, who is holding the title of COO and/or president at the time. Literature has categorized CEO succession as a relay, horse race, or outside succession based on presence or lack of an heir apparent.	Behn, Riley Jr. & Yang (2005); Canalla & Shen (2001); Shen & Canalla Jr. (2003); Zhang & Rajagopalan (2004)

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Incumbent CEO Founder	Binary variable (0, 1) indicates whether the incumbent CEO was a founder (1) or not (0). Research shows if CEO is the founder, there is less CEO change.	Wasserman (2003)
Incumbent CEO Origin	Binary variable (0, 1) indicates whether the incumbent CEO was an internal (0) or external (1) hire. Parrino defines "internal" as someone having been with the company for at least a year prior to becoming CEO. Many studies have supported the impact that CEO origin can have on a firm and the firm's leadership.	Baran & Forst (2015); Bernard, Godard, & Zouaoui (2018); Georgakakis & Ruigrok (2017); Ishak, Ismail, Ku Nor Izah Ku, & Abdullah (2012); Lauterbach, Vu, & Weisberg (1999); Palomino & Peyrache (2013); Parrino (1997); Jalal & Prezas (2012); Sardeshmukh & Corbett (2011); Schwartz & Menon (1985)
Incoming CEO Undergraduate Degree	Binary variable (0, 1) indicating whether the incumbent CEO completed an undergraduate degree (1) or not (0). Research has shown that CEO education plays a role in the selection of a new CEO yet does not influence the decision to replace a CEO, nor does it affect the firm performance in the long-term. However, other research has shown that CEO education results in more risky and innovative business models.	Bhagat, Bolton, & Subramanian (2010); King, Srivastav, & Williams (2016)

VARIABLE NAME	VARIABLE DEFINITION & OPERATIONALIZATION	VARIABLE REFERENCES
Incoming CEO Graduate Degree	Binary variable (0, 1) indicating whether the incumbent CEO completed a graduate degree (1) or not (0). Research has shown that CEO education plays a role in the selection of a new CEO yet does not influence the decision to replace a CEO, nor does it affect the firm performance in the long-term. However, other research has shown that CEO education results in more risky and innovative business models.	Bhagat, Bolton, & Subramanian (2010); King, Srivastav, & Williams (2016)
Incoming CEO Origin	Binary variable (0, 1) indicates whether the incoming CEO is an internal (0) or external (1) hire. Parrino defines "internal" as someone having been with the company for at least a year prior to becoming CEO. Many studies have supported the impact that CEO origin can have on a firm and the firm's leadership.	See "Incumbent CEO Origin" References
Incoming CEO Previous CEO Experience	Binary variable (0, 1) indicates whether the incoming CEO had held at least one CEO position prior to current position (1) or not (0). Many studies have supported that a CEO's previous experience can influence market performance, firm financial performance, and even post-succession performance.	Bragaw & Misangyi (2017); Elsaid, Wang, & Davidson III (2011); Guthrie & Datta (1997); Hamori & Koyuncu (2015); Zhu & Shen (2016)
Incoming CEO Age	Refers to the age of the incoming CEO at time of succession event. Research has shown that CEOs of increasing age adopt less risky strategies.	Chowdhury & Fink (2017); Serfling (2014)
Change Free Cash Flow (Prior Year to Third Year)	Change free cash flow from year before succession to third year following	Rivolta (2018)

Conceptual Model and Hypotheses

In this section, a model is proposed to holistically evaluate succession predictors and their impact on succession lead time and, ultimately, firm performance. The conceptual model in Figure 6 shows a mediated model wherein lead time acts as a mediator.

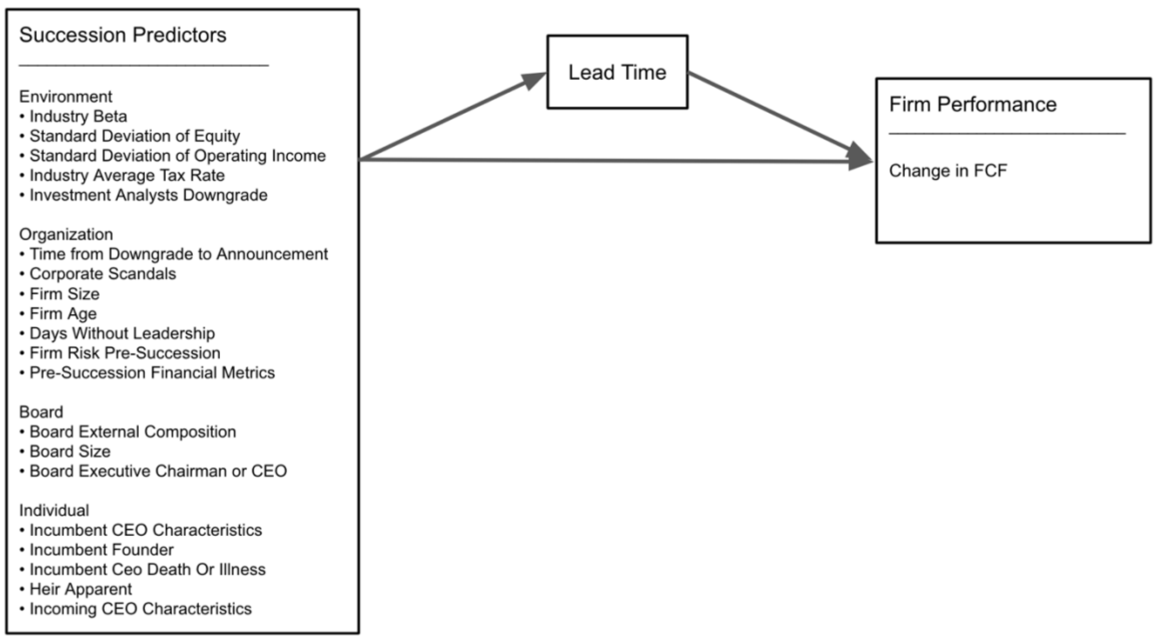

Figure 6. Conceptual Model

Lead time is proposed as a mediator as lead time could have an intermediary relationship with the predictors and firm performance. By designating lead time as a mediator, this research seeks to explain better the underlying relationships between the other predictor variables and firm performance. With lead time having only been recently introduced as a critical variable in succession research (Rivolta, 2018), this current study examines the variable and its interactions with other common variables.

Theory supports the notion that lead time may significantly influence the impact that other variables have on firm performance. Bounded rationality is a perspective that acknowledges the impossibility of clearly identifying all potential solutions during the planning process. Furthermore, having more time to plan and execute plans is hazardous and becomes increasingly hazardous in longer time frames (March & Simon, 1958). Additionally, Kunisch, Bartunek, Mueller, and Huy (2017) point out that, with respect to outcomes, neither “slower is better” nor “faster is better” always apply. For example, Zhang and Rajagopalan (2010) determined that the relationship between the pace of change and performance is an inverted U-shape and that *too much* change in a short time is disruptive and ineffective. Further speaking to the effect of lead time, they also find that fast-paced change (ex. short lead time) does not ensure successful, long-lasting strategic change. The time that an organization has to prepare for and execute a CEO succession most certainly affects how other factors would affect firm performance.

The lead time of a CEO succession event has a definitive impact on the performance of a company. Previous research has explored and sought further understanding of this impact. For example, Harvey and Evans (1994) and Quigley, Crossland, and Campbell (2017) each highlight the importance of succession planning in the context of sudden or otherwise unexpected CEO deaths or departures, with each showing a definitive firm impact and resultant market reaction. Furthermore, Rivolta (2018), in exploring CEO retirements, found that longer lead times are associated with favorable stock performance and firm financial performance.

The conceptual model (see Figure 6 above), presented in this research for comparative analysis by traditional linear regression, draws from Rivolta’s (2018) analysis of the effect of lead time by exploring succession without the restraint of retirement as a cause and further incorporates previously presented predictor variables (see Figure 1) as presented by Berns and Klarner (2017), with firm performance as defined by Hamori and Koyuncu (2015) and Rivolta (2018). Thus, the following hypotheses are posited:

> **Hypothesis 1:** Succession event lead time is positively related to post-succession firm performance.
>
> **Hypothesis 2:** Succession event lead time positively mediates the impact of succession event predictors on firm performance.

Rivolta (2018) notes that a firm's performance following a succession event is most benefited by a longer lead time preceding the succession event. This current study posits that there is a length of time in which increasing lead times no longer result in increased firm performance, per the law of diminishing returns.

The variables presented (see Table 4) demonstrate the many predictors to CEO succession that have been researched singularly and in small combinations, many with differing and diverging conclusions. This current research forms a comprehensive understanding of the many predictors and how they interact with one another.

> **Hypothesis 3:** The predictor variables in Table 3 will be found to have the predicted relationship strengths and directions indicated in relation with the firm performance outcome of change in ROA.

Table 4. Summary of Predictor Variables

VARIABLE NAME	PREDICTED RELATIONSHIP STRENGTH	PREDICTED RELATIONSHIP DIRECTION
Lead Time	Strong	+
Beta (Industry)	Low	-
Standard Deviation of Equity (Industry)	Low	-
Standard Deviation of Operating Income (Industry)	Strong	-
Average Tax Rate (Industry)	Low	-
Investment Analyst Downgrade	Moderate	+
Time from Downgrade to Announcement	Moderate	-
Pre-Succession ROA	Moderate	+
Pre-Succession Income	Strong	+
Natural Log of Assets	Low	-
Corporate Scandals	Moderate	-
Firm Size	Moderate	+
Firm Age	Low	+
Days Without Leadership	Moderate	-
Board Size	Low	+
Board External Composition	Moderate	-
Board Executive Chairman or CEO	Moderate	-
Incumbent CEO Age	Moderate	-
Incumbent CEO Tenure	Low	+
Incumbent CEO Undergraduate Degree	Low	+
Incumbent CEO Graduate Degree	Low	+
Incumbent CEO Previous CEO Experience	Strong	+
Unexpected CEO Death or Illness	Strong	-
Incumbent CEO Founder	Moderate	-
Incumbent CEO Origin	Moderate	+
Heir Apparent	Low	+
Incoming CEO Undergraduate Degree	Low	+
Incoming CEO Graduate Degree	Moderate	+
Incoming CEO Origin	Strong	+
Incoming CEO Previous CEO Experience	Moderate	-
Incoming CEO Age	Low	+

Relationship strength: low correlation $r < .12$, moderate $r = .13 - .25$, high $r > .26$ (Cohen, 1992)

CHAPTER III

METHODOLOGY

To better evaluate the most commonly accepted predictors of CEO succession (Berns & Klarner, 2017), as well as to answer the many calls to incorporate big data methods into organizational leadership research (McAbee et al., 2017; Tonidandel et al., 2016; Wenzel & Van Quaquebeke, 2018), this current research undertakes a dual-methodological approach to CEO succession analyzing the same manually collected dataset of CEO turnovers from 2014 to 2016.

The analyses are performed using both traditional linear regression design and contemporary machine learning design to evaluate succession event predictors' impact on succession event lead time, and in turn, the effect on firm performance using both methodologies as such dual-methodological analyses are scarce particularly in this literature. In some examples of the literature, such as the analyses applied in the current study, this approach has demonstrated that variables deemed less relevant in one given methodology can be relevant and significant when analyzed using a different methodological approach (Alonso-Dos-Santos and Llanos-Contreras, 2019; Escamilla-Fajardo, Alguacil, and Gómez-Tafalla, 2021; Hernández-Perlines, Moreno-García, and Yañez-Araque, 2016).

Data and Sample

Succession events comprising the initial dataset are S&P 500 companies that experienced a CEO departure during 2014–2016, as retrieved from Execucomp. Departures were excluded wherein the incumbent CEO did not serve for at least one year, following comparative research that requires a full year of firm performance under the leadership of the incumbent CEO prior to departure for proper evaluation of the effect of the departure on firm performance (Rivolta, 2018). Additional stock and accounting information is gathered from Compustat. EDGAR provides proxy statements and CEO appointment dates and tenure with the company. BoardEx provides board composition information. Bloomberg provides additional CEO career information. The resulting dataset follows the data dictionary presented in Table 5.

Data from the various sources were manually assembled into a single dataset, with number formats remaining as presented originally for much of the data. Binary values were used to represent binary phenomena; for example, if an incoming CEO had completed a graduate-level education at the time of succession, that data was indicated by a “1”, while an incoming CEO lacking an advanced degree was indicated “0”.

Each row of the dataset represents all variables of a single succession event as analyzed by both methodologies, meaning that a single row contained Environment variables, Organization variables, Board variables, and Individual variables.

Table 5. Data Dictionary

VARIABLE	FIELD NAME	DATA TYPE	DESCRIPTION
Lead Time	Leadtime	Days	Days from the announcement of CEO departure to CEO end date.
Beta (Industry)	IndBeta	Number	Average stock Beta for calendar year preceding succession event.
Standard Deviation of Equity (Industry)	InSdEqt	Percent	Industry
Standard Deviation of Operating Income (Industry)	InSdOpIn	Percent	Industry
Average Tax Rate (Industry)	IndTax	Percent	Industry
Investment Analyst Downgrade	Inv_DnB	Binary	0 = no; 1 = yes
Time from Downgrade to Announcement	Down_ann	Integer	Days from most recent downgrade until succession announcement.
Pre-Succession ROA	ROA_pre	Percent	Calculated ROA
Pre-Succession Income	Inc_pre	Number	Number in millions USD.
Natural Log of Assets	LnAsset	Number	Natural log of book value of pre-succession assets as a proxy for complexity of incumbent CEO's job.
Corporate Scandals	Corpscan	Binary	0 = no; 1 = yes
Firm Size	Mrkt_cap	Number	In billions USD
Firm Age	Firm_age	Integer	Years
Days Without Leadership	No_lead	Integer	Days
Board Size	Brd_size	Integer	Board Size
Board External Composition	Brd_ext	Percent	Board External Composition
Board Executive Chairman or CEO	Brd_chr	Binary	Executive Chairman present on Board or Combined role of CEO & Chairman is present (1- Yes, 0 - No)
Incumbent CEO Age	Old_age	Integer	Incumbent CEO Age at Time of Succession
Incumbent CEO Tenure	Old_ten	Number	Years
Incumbent CEO Undergraduate Degree	Old_bach	Binary	0 = no; 1 = yes
Incumbent CEO Graduate Degree	Old_grad	Binary	0 = no; 1 = yes
Incumbent CEO Prior CEO Experience	Oldceoex	Binary	0 = no; 1 = yes
Unexpected CEO Death or Illness	Unex_di	Binary	0 = no; 1 = yes

VARIABLE	FIELD NAME	DATA TYPE	DESCRIPTION
Incumbent CEO Founder	Founder	Binary	0 = no; 1 = yes
Incumbent CEO Origin	Old_orig	Binary	0 = internal; 1 = external
Heir Apparent	Heirapp	Binary	0 = no; 1 = yes
Incoming CEO Undergraduate Degree	New_bach	Binary	0 = no; 1 = yes
Incoming CEO Graduate Degree	New_grad	Binary	0 = no; 1 = yes
Incoming CEO Origin	New_orig	Binary	0 = internal; 1 = external
Incoming CEO Prior CEO Experience	Newceoex	Binary	0 = no; 1 = yes
Incoming CEO Age	New_age	Integer	Incoming CEO Age at Time of Succession
Change FCF 0-3	ChFCF3	Percent	Change free cash flow from the year before succession to the third year following.

Traditional Linear Regression Study Design

To assess the models (Figures 6, 7, and 8) with traditional linear regression, the data set's data are first tested for multicollinearity. Multivariate regression analysis is then performed to examine the many variables included among the succession predictors. By regressing the succession predictors onto lead time and firm performance, the multiple variables are observed in interdependence. Finally, the model's fit to the data is tested using traditional structural equation model fit indices. The traditional regression design tests hypotheses one, two, and three.

Contemporary Machine Learning Study Design

The KNIME analytics platform is used to build machine learning models. KNIME is an open-source platform for data analytics that integrates various components for machine learning and data mining functionality using a graphical, workflow-like user interface for modeling, data analysis, and visualization. In this research, analyses are performed using decision trees and random forest algorithmic implementation within KNIME. These analyses benefit from not requiring normalization or scaling of input data. They are suitable to work on various data types (categorical, continuous, binary), they are easy to interpret, and create powerful and accurate models on many different problems and research questions.

Decision trees are one of the most commonly used machine learning algorithms due to their lucidity and simplicity (Piryonesi & El-Diraby, 2020; Wu, Kumar, Quinlan et al., 2008). Decision trees are built by splitting the initial data into subsets, or *children*, based on splitting rules determined algorithmically based on variable importance. Each derived subset is then split again until the recursion is complete, which occurs when splitting no longer adds predictive value (Quinlan, 1986).

While a decision tree algorithm generates a single tree, random forests lead to more reliable conclusions by aggregating many decision trees to limit overfitting and error due to bias, yielding more useful results (Ho, 1995, 1998). Random forest analyses have been shown to achieve a high prediction accuracy, in addition to providing descriptive measures of variable importance to indicate the relative importance of each variable, both in interactions and main effects (Strobl, Malley, & Tutz, 2009).

To ensure the highest quality of binary splits at each node, the Gini Index is used, which seeks to minimize the misclassification of data. The Gini Index has been established in economics for use in decision tree analysis. It is used to determine the purity of a given split class derived from a node, identifying the optimal split as one that increases the purity of the classes derived from the node (Sharda, Delen, & Turban, 2016). The Gini Index is derived from Gini Impurity, which is defined as one minus the sum of squares of the class probabilities within a dataset. In this calculation, p is the entire dataset, *N* is the number of classes, and p_i is the frequency of class *i* in the dataset (Sharda et al., 2016).

$$\textit{Gini Impurity}\ (\mathrm{p}) = 1 - \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{p}_{\mathrm{i}}^{2}$$

The Gini Index is then calculated as the weighted sum of the calculated Gini Impurity of the various subsets created following a split, with each portion being weighted by the ratio of the size of the *child* subset data in relation to the size of the *parent* dataset.

$$\text{Gini Index} = \sum_{j=1}^{K} w_j\ \textit{Gini Impurity}\ (j,\ after)$$

$$w_j = \frac{\#\ \text{data in subset}\ (j, after)}{\#\ \text{data in dataset}\ (before)}$$

In this case, *K* is the number of subsets created at a split (in this research, always two subsets per split), and (*j, after*) is subset *j* following a split (Melcher & Silipo, 2020).

Cross-Validation for Model Assessment

K-fold cross-validation is used in the testing of the data in lieu of traditional single-split partitioning in order to yield a more objective assessment of the prediction accuracy for a given data set and prediction model (Cho, Kim, Jeong et al., 2021). In the decision tree analysis of this research, the value of k is set to 10, following the guidelines presented in Arlot and Celisse (2010). This means that to produce one decision tree (see Figure 8 in Chapter IV), a process is repeated ten times automatically where a small sample is “pulled” from the complete dataset, which is used to “learn,” after which the remaining data is tested according to what the sample determined was most reflective of the overall model. Decision tree analysis indicates which of the many succession predictor variables are the most important to the model, thereby informing hypotheses one, two, and three.

In addition to having very strong predictive capacity, random forests can also be used to rank the importance of variables in a given model, following a standard manual calculation procedure based on the usage/split statistics. Whereas random forests are comprised of many individual decision trees, the usage statistics of the variables in each tree (how many times a given variable is algorithmically selected to split the data at each of the first three-level splits) is divided by the total number of opportunities the variables each have to act as a split (the resulting values are weighted in descending order beginning with the first split). The resulting value is normalized, with the highest value being the variable of greatest importance.

Decision Tree Ensembles, also referred to as random forests in most commonly used variants, are useful for feature selection in addition to being effective classifiers. One approach to dimensionality reduction is to generate a large and carefully constructed set of trees against a target attribute and then use each attribute’s usage statistics to find the most informative subset of features. Specifically, we can generate a large set (2,000) of very shallow trees (two levels), with each tree being trained on a small fraction (three) of the total number of attributes. If an attribute is often selected as the best split, it is most likely an informative feature to retain. A score calculated on the attribute usage statistics in the random forest tells us — relative to the other attributes — which are the most predictive attributes.

At the conclusion of the machine learning analysis, results from the machine learning design are then compared with the multivariate regression design. A primary contribution of this research demonstrating the application of a contemporary machine learning methodology alongside traditional linear regression, with the objective to introduce CEO succession research to another acceptable methodology (Haig, 2020).

CHAPTER IV

RESULTS

This chapter presents the results of the research and analyses from both traditional regression and machine learning research designs. Descriptive statistics, including means, standard deviations, and Pearson correlations, are presented in Table 6.

Several values for the variable Investment Analyst Downgrade were imputed to preserve the dataset. Values were *missing not at random*, as the corresponding companies were not publicly traded before the succession event.

Von Hippel (2004) suggests multiple imputations instead of single imputation; therefore, multiple imputations were performed in SPSS following guidelines presented by IBM (2020) and Little and Rubin (1987). Following the descriptive statistics are an analysis of correlation and collinearity, a summary of the linear regression and machine learning analyses, and a series of figures and tables illustrating the results of this study.

Table 6. Means, Standard Deviations, and Pearson Correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Beta (Industry)	1.093	0.356	--																
2 Standard Deviation of Equity (Industry)	0.395	0.156	.488**	--															
3 Standard Deviation of Operating Income (Industry)	0.333	0.333	0.130	0.069	--														
4 Average Tax Rate (Industry)	0.091	0.057	-0.105	-.555**	0.065	--													
5 Investment Analyst Downgrade	0.68	0.47	0.050	-0.104	-0.149	0.055	--												
6 Time from Downgrade to Announcement	167.892	188.835	-0.130	-0.002	0.076	-0.063	-.736**	--											
7 Pre-Succession ROA	0.10	0.09	.244**	.276**	-0.021	-0.017	0.063	-0.084	--										
8 Pre-Succession Income	2864.40	5060.35	0.103	-0.005	.188*	0.159	0.026	-0.020	.186*	--									
9 Natural Log of Assets	9.705	1.335	-0.158	-.280**	.206*	.297**	-0.036	0.096	-.181*	.647**	--								
10 Corporate Scandals	0.03	0.18	0.093	0.044	0.065	0.038	0.028	-0.006	-0.042	.255**	.181*	--							
11 Firm Size	35.649	55.727	0.154	0.107	0.164	0.086	0.034	-0.026	0.138	.859**	.576**	0.161	--						
12 Firm Age	72.772	49.867	-0.107	-.186*	-0.145	.246**	-0.004	0.024	-0.106	0.067	.271**	-0.032	-0.044	--					
13 Time Without Leadership	3.173	23.729	0.095	-0.035	-0.070	-0.016	-0.010	-0.037	-0.028	-0.056	-0.076	-0.024	-0.065	-0.003	--				
14 Board Size	11.047	2.333	-0.055	-0.145	0.044	0.154	-0.109	0.163	-0.014	.270**	.414**	0.132	.224*	.287**	-0.090	--			
15 Board External Composition	0.830	0.107	-0.159	-0.167	-0.030	0.130	0.054	-0.034	-0.046	0.113	0.097	0.008	0.054	0.017	0.072	0.025	--		
16 Board Executive Chairman or CEO	0.504	0.502	0.055	0.081	0.047	0.116	0.056	0.005	0.078	0.170	0.174	-0.092	0.153	.180*	-0.121	0.034	-.231**	--	
17 Incumbent CEO Age	61.213	5.229	-0.010	-0.062	0.043	0.122	-0.130	0.105	-0.008	0.088	0.069	-.198*	0.008	0.117	0.038	-0.076	-0.082	.201*	--
18 Incumbent CEO Tenure	9.727	5.677	-0.042	0.061	0.075	-0.018	0.039	-0.084	.209*	0.028	-0.106	-0.165	-0.022	-0.117	-0.009	-0.174	-0.101	.214*	.238**
19 Incumbent CEO Undergraduate Degree	0.992	0.089	0.008	-0.066	0.044	-0.031	0.129	-0.033	-0.090	0.031	0.066	0.016	0.039	0.044	0.012	0.117	.378**	-0.088	-.236**
20 Incumbent CEO Graduate Degree	0.693	0.463	0.046	-0.083	0.015	-0.063	0.051	0.088	0.013	-0.014	0.084	-0.075	-0.052	0.021	0.084	-0.009	0.087	0.125	.234**
21 Incumbent CEO Previous CEO Experience	0.268	0.445	-0.035	-0.018	0.009	0.026	-0.039	-0.012	-0.098	-0.036	0.070	-0.007	-0.083	-0.015	-0.074	-0.005	-0.006	-.218*	-0.096
22 Incumbent CEO Unexpected Death or Illness	0.039	0.195	-0.093	-0.087	-0.027	0.113	-0.033	0.017	-0.120	0.064	.227*	-0.037	-0.024	.256**	.374**	0.066	0.163	-0.042	0.101
23 Incumbent CEO Founder	0.039	0.195	-0.035	0.038	-0.043	-0.052	-0.033	0.035	0.100	-0.040	-0.033	-0.037	-0.002	-0.171	-0.024	0.013	-.252**	0.120	.209*
24 Incumbent CEO Origin	0.283	0.452	0.020	0.124	-0.036	-0.065	-0.051	-0.001	-0.055	-0.028	-0.023	-0.013	-0.082	-0.002	-0.080	-0.073	-0.005	-0.075	0.045
25 Heir Apparent	0.575	0.496	0.123	-0.025	-0.033	0.161	-0.083	0.044	0.050	-0.054	-0.037	-0.027	-0.161	.185*	-0.048	.175*	-0.069	0.134	0.053
26 Incoming CEO Undergraduate Degree	0.984	0.125	-0.095	-0.106	0.033	0.024	-0.087	0.088	0.115	0.065	0.085	0.023	0.037	0.058	0.017	0.030	0.131	-0.125	0.042
27 Incoming CEO Graduate Degree	0.575	0.496	-0.083	0.022	0.003	-0.107	-0.015	0.026	0.107	0.113	0.042	0.064	0.084	-0.063	-0.054	0.045	0.078	-0.121	-0.112
28 Incoming CEO Origin	0.150	0.358	0.118	0.149	-0.040	-0.121	0.101	-0.056	0.060	-0.065	-.195*	-0.076	-0.049	-0.081	0.164	-0.085	0.115	-0.158	0.072
29 Incoming CEO Previous CEO Experience	0.268	0.445	0.052	0.054	-0.029	-0.078	0.151	-0.174	-0.025	-0.028	0.025	-0.007	-0.023	-0.067	0.099	-0.005	0.030	-0.111	-0.096
30 Incoming CEO Age	53.496	6.177	0.059	-0.002	-0.022	0.077	0.149	-0.120	0.013	-0.008	-0.008	0.132	-0.021	0.011	0.049	0.126	0.039	-0.022	0.042
31 Lead Time	94.945	103.810	-0.014	0.148	-0.002	-0.111	-0.103	-0.034	0.168	-0.098	-0.093	-0.166	-0.075	0.016	-0.050	-0.046	0.059	-0.068	0.003
32 Change Free Cash Flow (Prior Year to Third Year)	0.626	3.398	0.095	.207*	-0.049	-0.172	-0.088	0.025	-.215*	-0.071	-.248**	-0.008	-0.047	-0.135	-0.004	-0.128	-0.048	0.040	.187*

*** Correlation is significant at the 0.01 level (2-tailed).*

** Correlation is significant at the 0.05 level (2-tailed).*

Table 6 (continued). Means, Standard Deviations, and Pearson Correlations

Variable	Mean	SD	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
1 Beta (Industry)	1.093	0.356															
2 Standard Deviation of Equity (Industry)	0.395	0.156															
3 Standard Deviation of Operating Income (Industry)	0.333	0.333															
4 Average Tax Rate (Industry)	0.091	0.057															
5 Investment Analyst Downgrade	0.68	0.47															
6 Time from Downgrade to Announcement	167.892	188.835															
7 Pre-Succession ROA	0.10	0.09															
8 Pre-Succession Income	2864.40	5060.35															
9 Natural Log of Assets	9.705	1.335															
10 Corporate Scandals	0.03	0.18															
11 Firm Size	35.649	55.727															
12 Firm Age	72.772	49.867															
13 Time Without Leadership	3.173	23.729															
14 Board Size	11.047	2.333															
15 Board External Composition	0.830	0.107															
16 Board Executive Chairman or CEO	0.504	0.502															
17 Incumbent CEO Age	61.213	5.229															
18 Incumbent CEO Tenure	9.727	5.677	--														
19 Incumbent CEO Undergraduate Degree	0.992	0.089	-0.144	--													
20 Incumbent CEO Graduate Degree	0.693	0.463	0.132	0.134	--												
21 Incumbent CEO Previous CEO Experience	0.268	0.445	-.258**	0.054	-0.022	--											
22 Incumbent CEO Unexpected Death or Illness	0.039	0.195	-0.052	0.018	0.047	-0.031	--										
23 Incumbent CEO Founder	0.039	0.195	.476**	-.440**	-0.041	-0.031	-0.041	--									
24 Incumbent CEO Origin	0.283	0.452	-.195*	-0.142	0.002	.369**	0.142	-0.037	--								
25 Heir Apparent	0.575	0.496	.204*	0.104	0.014	-0.020	-0.153	0.092	-.201*	--							
26 Incoming CEO Undergraduate Degree	0.984	0.125	0.033	-0.011	.190*	-0.066	0.026	0.026	-0.061	0.019	--						
27 Incoming CEO Graduate Degree	0.575	0.496	-0.079	-0.077	0.083	0.124	-0.072	-0.072	0.046	-0.031	0.147	--					
28 Incoming CEO Origin	0.150	0.358	0.009	0.037	0.040	-0.004	0.142	0.029	.226*	-.398**	0.053	-0.041	--				
29 Incoming CEO Previous CEO Experience	0.268	0.445	-.176*	0.054	-0.060	.277**	0.060	-0.031	.212*	-.271**	0.076	-0.020	.395**	--			
30 Incoming CEO Age	53.496	6.177	-.298**	.181*	0.018	0.000	0.003	-0.168	0.043	-0.120	0.103	-0.140	0.131	.330**	--		
31 Lead Time	94.945	103.810	0.121	0.053	-0.161	-0.004	-0.083	0.034	-0.030	-0.078	0.100	0.140	0.098	0.032	-0.151	--	
32 Change Free Cash Flow (Prior Year to Third Year)	0.626	3.398	-0.052	0.015	0.070	-0.030	-0.036	-0.033	.257**	-0.172	-0.149	-0.098	.274**	-0.034	0.059	-0.101	--

*** Correlation is significant at the 0.01 level (2-tailed).*

** Correlation is significant at the 0.05 level (2-tailed).*

Correlation and Collinearity Analysis

The correlation coefficients between the variables shown in Table 6 are computed using Pearson's correlation coefficient, as it is the most commonly used coefficient for analyzing correlations (Urdan, 2010) and is found throughout succession literature. Table 8 provides a summary of how the correlations observed are both consistent and inconsistent with existing research.

Correlation coefficients in Table 6 are within the bounds which Field (2005) suggests as the threshold of multicollinearity (0.8), with the sole exception being .803 between firm size and time from downgrade to announcement. Kleinbaum, Kupper, and Muller (1988) suggest testing for multicollinearity using both the Variance Inflation Factor (VIF) and the Tolerance test.

Presented in Table 7, all VIF values are less than 10 (Myers, 1990), and all Tolerance values are greater than .1 (Menard, 1995), indicating no problems with multicollinearity and no concern that the predictive variables excessively influence one another.

Table 7. Coefficients and Collinearity Statistics

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
(Constant)	1.948	7.696		0.253	0.801		
Lead Time	-0.003	0.003	-0.092	-0.994	0.323	0.720	1.389
Beta (Industry)	-0.340	0.999	-0.036	-0.340	0.735	0.558	1.792
Standard Deviation of Equity (Industry)	4.144	2.865	0.191	1.447	0.151	0.353	2.831
Standard Deviation of Operating Income (Industry)	-0.765	0.889	-0.075	-0.860	0.392	0.807	1.239
Average Tax Rate (Industry)	3.157	6.846	0.053	0.461	0.646	0.471	2.125
Investment Analyst Downgrade	-1.451	0.932	-0.200	-1.557	0.123	0.370	2.704
Time from Downgrade to Announcement	-0.003	0.002	-0.152	-1.200	0.233	0.384	2.603
Pre-Succession ROA	-13.629	3.720	-0.356	-3.664	0.000	0.648	1.544
Pre-Succession Income	0.000	0.000	0.301	1.518	0.132	0.156	6.414
Natural Log of Assets	-1.003	0.368	-0.394	-2.723	0.008	0.293	3.417
Corporate Scandals	0.184	1.764	0.009	0.104	0.917	0.739	1.353
Firm Size	-0.005	0.011	-0.075	-0.398	0.692	0.173	5.776
Firm Age	-0.006	0.007	-0.089	-0.908	0.366	0.639	1.565
Time Without Leadership	-0.003	0.013	-0.024	-0.260	0.796	0.739	1.353

	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Board Size	0.072	0.143	0.049	0.501	0.617	0.637	1.569
Board External Composition	-2.109	3.012	-0.066	-0.700	0.485	0.686	1.458
Board Executive Chairman or CEO	0.584	0.648	0.086	0.901	0.370	0.670	1.493
Incumbent CEO Age	0.115	0.063	0.177	1.840	0.069	0.661	1.514
Incumbent CEO Tenure	-0.052	0.069	-0.086	-0.753	0.453	0.467	2.142
Incumbent CEO Bachelor	5.808	4.196	0.152	1.384	0.170	0.510	1.959
Incumbent CEO Graduate	0.646	0.705	0.088	0.917	0.362	0.664	1.506
Incumbent CEO Previous CEO Experience	-0.533	0.752	-0.070	-0.709	0.480	0.633	1.580
Incumbent CEO Unexpected Death or Illness	-1.275	1.733	-0.073	-0.736	0.464	0.618	1.618
Incumbent CEO Founder	0.480	1.923	0.028	0.250	0.803	0.502	1.992
Incumbent CEO Origin	1.451	0.708	0.193	2.048	0.043	0.689	1.451
Heir Apparent	-0.929	0.748	-0.136	-1.242	0.217	0.514	1.947
Incoming CEO Bachelor	-1.324	2.397	-0.049	-0.553	0.582	0.789	1.268
Incoming CEO Graduate	-0.211	0.600	-0.031	-0.351	0.726	0.797	1.255
Incoming CEO Origin	1.975	0.986	0.208	2.004	0.048	0.568	1.760
Incoming CEO Previous CEO Experience	-1.140	0.765	-0.149	-1.490	0.139	0.612	1.633
Incoming CEO Age	-0.002	0.054	-0.004	-0.040	0.968	0.644	1.553

Dependent Variable: Change in Free Cash Flow from Prior Year to the Third Year Following Succession.

Traditional Linear Regression Summary

The hypotheses were tested using correlations and multivariate regressions, utilizing both SPSS and Mplus. Hypothesis 1 is not supported, with succession event lead time lacking a significant correlation with post-succession firm performance. The Pearson correlation between the two variables is -.101 (p-value .261). Hypothesis 2 is not supported for any predictor variable, as no indirect effect is statistically significant. The results of Hypothesis 3 are mixed, as presented in Table 8.

Table 8. Relationship Strength and Direction Results

VARIABLE NAME	PREDICTED RELATIONSHIP STRENGTH	STRENGTH HYPOTHESIS	PREDICTED RELATIONSHIP DIRECTION	DIRECTION HYPOTHESIS
Lead Time	Strong	Low	+	Not Supported
Beta (Industry)	Low	Low	-	Not Supported
Standard Deviation of Equity (Industry)	Low	* Moderate	-	Not Supported
Standard Deviation of Operating Income (Industry)	Strong	Low	-	Supported
Average Tax Rate (Industry)	Low	Moderate	-	Supported
Investment Analyst Downgrade	Moderate	Low	+	Not Supported
Time from Downgrade to Announcement	Moderate	Low	-	Not Supported
Pre-Succession ROA	Moderate	* Moderate	+	Not Supported
Pre-Succession Income	Strong	Low	+	Not Supported

VARIABLE NAME	PREDICTED RELATIONSHIP STRENGTH	STRENGTH HYPOTHESIS	PREDICTED RELATIONSHIP DIRECTION	DIRECTION HYPOTHESIS
Natural Log of Assets	Low	** Moderate	-	Supported
Corporate Scandals	Moderate	Low	-	Supported
Firm Size	Moderate	Low	+	Not Supported
Firm Age	Low	Moderate	+	Not Supported
Days Without Leadership	Moderate	Low	-	Supported
Board Size	Low	Low	+	Not Supported
Board External Composition	Moderate	Low	-	Supported
Board Executive Chairman or CEO	Moderate	Low	-	Not Supported
Incumbent CEO Age	Moderate	* Moderate	-	Not Supported
Incumbent CEO Tenure	Low	Low	+	Not Supported
Incumbent CEO Undergraduate Degree	Low	Low	+	Supported
Incumbent CEO Graduate Degree	Low	Low	+	Supported
Incumbent CEO Previous CEO Experience	Strong	Low	+	Not Supported
Unexpected CEO Death or Illness	Strong	Low	-	Supported
Incumbent CEO Founder	Moderate	Low	-	Supported
Incumbent CEO Origin	Moderate	** Moderate	+	Supported
Heir Apparent	Low	Moderate	+	Not Supported
Incoming CEO Undergraduate Degree	Low	Moderate	+	Not Supported

VARIABLE NAME	PREDICTED RELATIONSHIP STRENGTH	STRENGTH HYPOTHESIS	PREDICTED RELATIONSHIP DIRECTION	DIRECTION HYPOTHESIS
Incoming CEO Graduate Degree	Moderate	Low	+	Not Supported
Incoming CEO Origin	Strong	** High	+	Supported
Incoming CEO Previous CEO Experience	Moderate	Low	-	Supported
Incoming CEO Age	Low	Low	+	Supported

Relationship strength: low correlation r < .12, moderate r = .13 - .25, high r > .26 (Cohen, 1992)
** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

Conceptual Models A, B, and C were tested to assess the models' fit to the data, with global fit statistics presented in Table 9. Initially, Models A and C presented fit statistics indicating a perfect fit, *just-identified* models unable to return global fit statistics. To obtain fit statistics for Models A and C, the value of a single variable known to have minimal impact on the model, New CEO Undergraduate Education, is fixed to its known value. While Mplus is typically adept at deciding which parameters should be freed and which should be fixed, occasionally, a model is not identified correctly by default, a problem that can be remedied by fixing one path.

Table 9. Model Fit Index

Model	R-Square	Two-Tailed P-Value	Chi-Square	df	P-Value	RMSEA	CFI	SRMR
A	0.426	0.002	178.362	30	0.0000	0.197	0.000	0.868
B	0.290	0	67.397	30	0.0001	0.099	0.243	0.088
C	0.420	0.000	178.362	30	0.0000	0.197	0.000	1.071

Further exploratory analysis yields several interesting insights. Whereas the predictors tested are categorized as either Environment, Organization, Board, and Individual predictors, the predictors of each individual category are regressed onto firm performance to assess which category most significantly affects firm performance: the resulting R-Squares of each category are .059 (Environment), .197 (Organization), .020 (Board), and .234 (Individual), suggesting that Individual predictors, in general, are the most impactful. Regressing only the predictors with correlations of significance at $p < .05$ with firm performance (variables: Standard Deviation of Equity, Pre-Succession ROA, Natural Log of Assets, Incumbent CEO Age, Incumbent CEO Origin, and Incoming CEO Origin) yields a model R-Square of .288, significant ANOVA (<.001), and significance in every coefficient, indicating a compelling model.

Contemporary Machine Learning Summary

The KNIME analytics platform (version 4.3.2) is used to test the models, with the objective of machine learning analysis not being to predict but rather to explain the interactions of the variables. Again, whereas a primary contribution of this research is comparing the application of a machine learning methodology with traditional linear regression in support of the need to introduce CEO succession research to another acceptable methodology (Haig, 2020), this analysis tests the same data and models as in the traditional analysis, as well as further post hoc analysis to demonstrate the analytical capabilities of machine learning and gain further theoretical insight.

The dependent variable, Change in Free Cash Flow from Year Prior to Succession to Third Year Following Succession, is converted to a binary format (0, 1) to perform machine learning analysis. A median-driven classification is created in order to parsimoniously classify successions as achieving outcomes above or below the median amongst firms included in the dataset (Iacobucci, Posavac, Kardes et al., 2015).

A method commonly used to evaluate the accuracy of such classification models is a graphical presentation called Receiving Operator Characteristics curve, or ROC curve. A ROC curve illustrates the quality and robustness of the model as defined by a false-positive rate (1-specificity) and true-positive rate (sensitivity). Figure 7 presents the ROC curve of all predictor variables, including Lead Time, as analyzed in both decision tree and random forest methods, indicating good model explanation, especially in the random forest analysis. The straight black line indicates what a random classifier would produce. The area under the curves is also indicated (.587 for decision tree; .622 for random forest). The closer the area is to 1.0, the better the model performance.

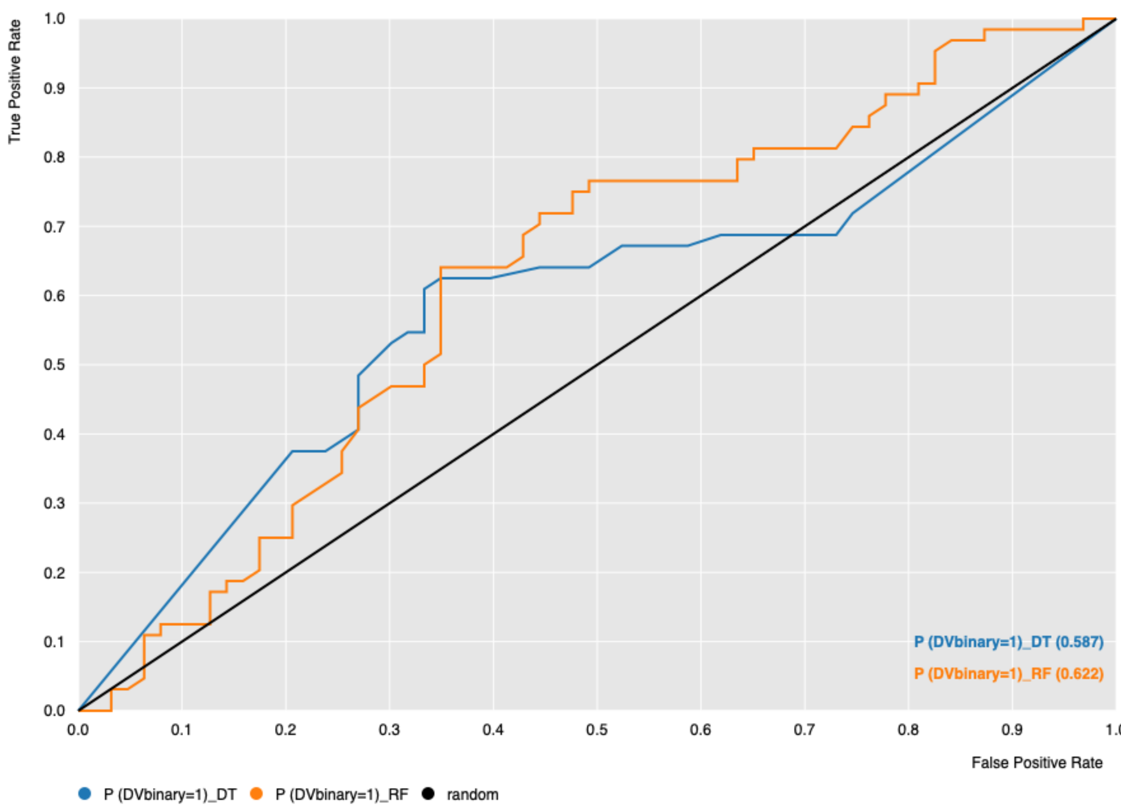

Figure 7. ROC Curve

The underlying relationships of the model variables are captured by the decision tree model, with accuracy exceeding 61%. The predictive power is acceptable given the subject matter being social phenomena, as well as due to the use of a smaller dataset. Figure 8 illustrates the decision tree generated. In support of Hypothesis 1, the variable *Leadtime* (Lead Time) is shown to be the most impactful to the model, with the split being 83.5 days, meaning that successions occurring within (less than or equal to) 83.5 days from the announcement of the departure of the incumbent CEO surprisingly result in a higher likelihood of long-term financial success for the firm. The next variables of greatest impact are the New CEO Age and Industry Tax, with Pre-Succession Income and Tenure of Incumbent CEO following.

Figure 8. Comprehensive Decision Tree

Whereas traditional regression yielded categorical R-Squares of .059 (Environment), .197 (Organization), .020 (Board), and .234 (Individual), suggesting that Individual predictors, in general, are the most impactful, decision trees of the same categories with the same variables included indicate predictive accuracies of 43.52% (Individual), 44.094% (Environment), 54.331% (Board), and 56.693% (Organization), giving support to the general strength of Environment and Board predictors, but suggesting that Organization predictors provide a better explanation of post-succession success than do Individual predictors.

While decision tree analysis produces a single decision tree based on *learned* algorithmic sampling and analyses, random forest analysis provides insights from many decision trees *trained* slightly differently from one another, resulting in more accurate and stable predictions. In this current analysis, the random forest is comprised of 500 unique decision trees. Random forest analysis, summarized in Figure 9, suggests that Lead Time is the variable of the greatest impact, followed by various firm-level and industry financial variables, firm age, and board size. Given the significant decrease in importance from Standard Deviation of Operating Income to Incumbent CEO Founder, a post hoc random forest analysis comprised of only the variables from Lead Time to Standard Deviation of Operating Income is run using 1,000 unique decision trees for improved accuracy given fewer variables, which results in a predictive model accuracy of 63.78% (traditional regression, analyzing the same variables, yields an R-square of .322). Furthermore, a post hoc ROC curve (see Figure 10) indicates an improved random forest model accuracy.

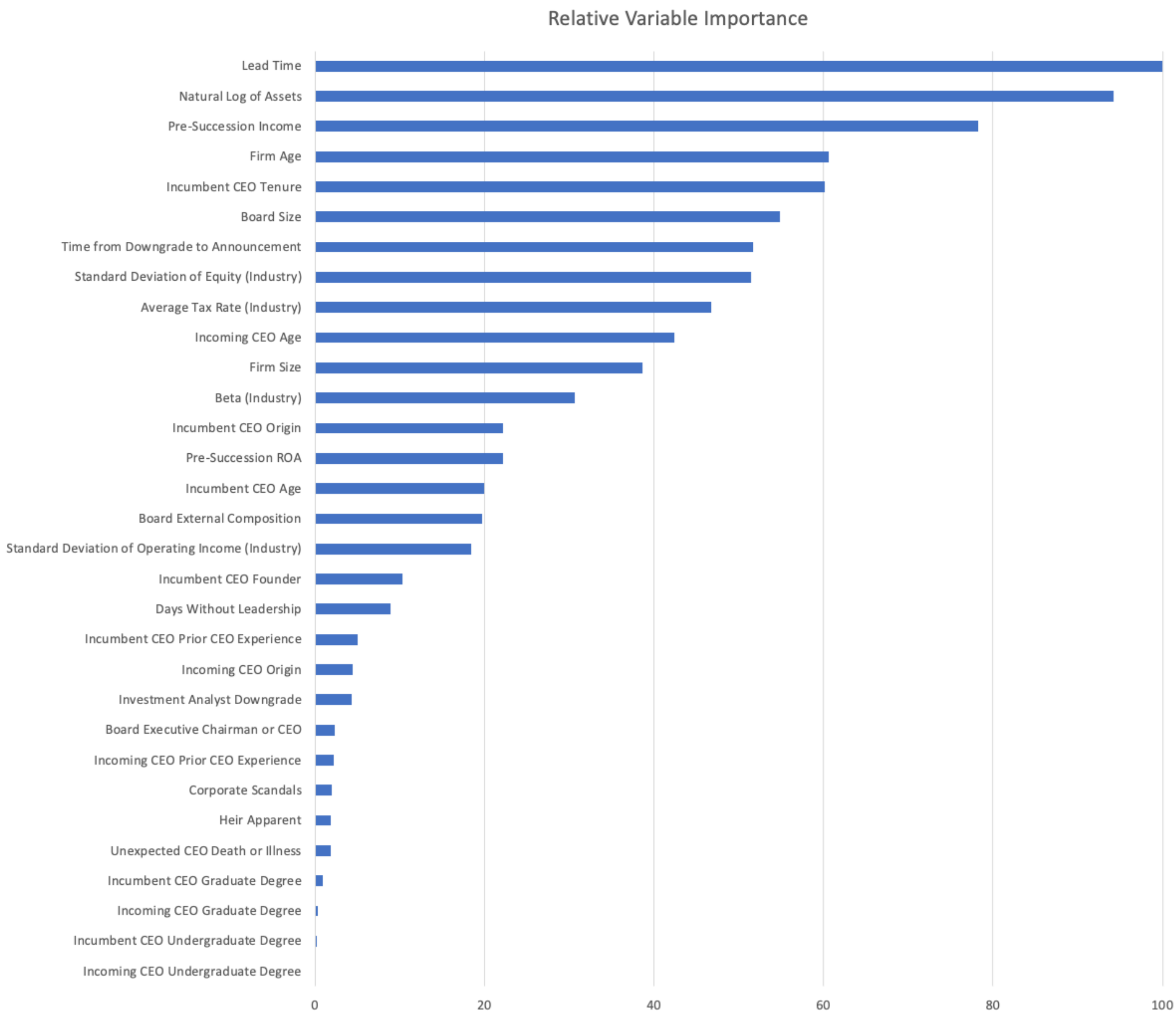

Figure 9. Random Forest Analysis: Relative Variable Importance

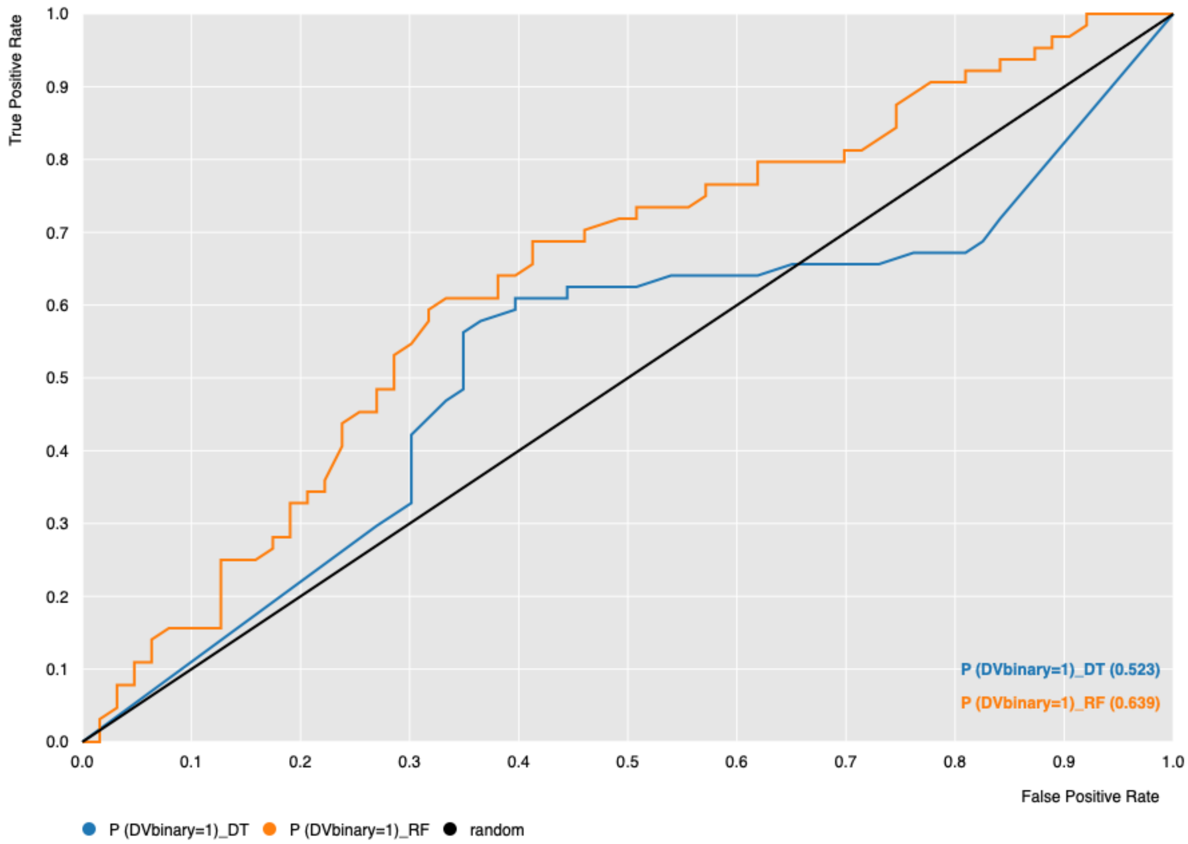

Figure 10. Post Hoc ROC Curve

Summary of Differing Outcomes

Traditional regression did not yield clarity of results due to just-identification and likely sample size. Machine learning analysis, especially that of random forest, produced a clearer and more reliable assessment of predictor explanation. Variable importance of traditional regression is calculated as the *part correlation*, squared to represent the decrease in total model R-square when each variable is removed from the complete model of all remaining variables. Table 10 presents the compared findings.

Table 10. Comparison of Traditional Regression and Machine Learning Analysis

SUCCESSION PREDICTORS	MULTIPLE REGRESSION		MACHINE LEARNING
	R-squared Change	VARIABLE IMPORTANCE	VARIABLE IMPORTANCE
Lead Time	0.0061	13	1
Natural Log of Assets	0.0454	2	2
Pre-Succession Income	0.0142	7	3
Firm Age	0.0050	16	4
Incumbent CEO Tenure	0.0035	18	5
Board Size	0.0015	23	6
Time from Downgrade to Announcement	0.0088	12	7
Standard Deviation of Equity (Industry)	0.0128	9	8
Average Tax Rate (Industry)	0.0013	24	9
Incoming CEO Age	0.0000	31	10
Firm Size	0.0010	25	11
Beta (Industry)	0.0007	27	12
Incumbent CEO Origin	0.0256	3	13
Pre-Succession ROA	0.0824	1	14
Incumbent CEO Age	0.0207	5	15
Board External Composition	0.0030	20	16
Standard Deviation of Operating Income (Industry)	0.0045	17	17
Incumbent CEO Founder	0.0004	28	18
Days Without Leadership	0.0004	29	19
Incumbent CEO Prior CEO Experience	0.0030	21	20
Incoming CEO Origin	0.0246	4	21
Investment Analyst Downgrade	0.0149	6	22
Board Executive Chairman or CEO	0.0050	15	23
Incoming CEO Prior CEO Experience	0.0137	8	24
Corporate Scandals	0.0001	30	25
Heir Apparent	0.0094	11	26
Unexpected CEO Death or Illness	0.0034	19	27
Incumbent CEO Graduate Degree	0.0052	14	28
Incoming CEO Graduate Degree	0.0007	26	29
Incumbent CEO Undergraduate Degree	0.0117	10	30
Incoming CEO Undergraduate Degree	0.0018	22	31

CHAPTER V

DISCUSSION

This research presents a valuable perspective to CEO and strategy research. With the Chief Executive Officer turnover rate at a record high (PricewaterhouseCoopers, 2019), it is expedient that organizations have a better understanding of CEO succession. A more holistic understanding of succession predictors can spur future research, while the introduction of machine learning as a methodological resource enhances the analytic potential of the field of study.

Implications

Strategy research, including CEO succession and corporate governance, should take advantage of the unique capabilities of machine learning in performing analyses. This current study supports previous research that has shown that when data present with moderate nonlinearity, traditional regression analysis produces inadequate performance, while decision tree techniques, as implemented in this study, result in a reduction of bias and improved coverage of (95%) confidence intervals (Lee, Lessler, & Stuart, 2010). Furthermore, Couronné, Probst, and Boulesteix (2018) conducted a large-scale benchmark experiment based on 243 datasets comparing the prediction performance of traditional regression with random forest analysis, finding random forest to produce more consistently accurate results. This current study finds that holistic analysis of common CEO succession predictors by a machine learning methodology more fully explains the predictors than does traditional linear regression.

This current research contributes interesting insights regarding the differences between linear regression and machine learning. In practice, traditional linear regression is more tedious in execution yet proved more effective in explaining relationships between variables. Conversely, machine learning analysis was simpler to carry out while resulting in highly accurate predictions. Ultimately, machine learning analysis yielded results that are more readily interpretable and applicable in organizations.

Previous researchers have focused on a wealth of variables that have been shown to have a significant effect on the financial success of a company during and following a change in executive leadership. In this research, a holistic analysis of multiple predictors has brought to light several impactful and practically applicable insights.

Lead time deserves recognition as a significant factor in the success of CEO succession and governance. Indeed, through machine learning analysis, lead time was shown to be the greatest predictor of future firm financial performance following a CEO change. Yet, only one other research project has made lead time the variable of interest in evaluating the effect of CEO successions on firm performance. Decision tree analysis indicates that the ideal lead time in a succession process is about 83 days, with a curvilinear relationship between lead time and performance. This suggests that significantly less or more than 83 days of lead time reduces an organization's performance, a conclusion that traditional linear regression did not yield. Rivolta (2018) found that the time from the announcement of a CEO's impending departure until the takeover date of the new CEO is significant and that improperly managed lead times lead to a considerable waste of financial resources. As Benjamin Franklin once said, "great haste makes great waste." It is imperative that organizations incorporate time expectations and frameworks into their succession planning process to ensure an effective leadership transition.

This research finds that the level of education of both the incumbent and incoming CEOs is virtually irrelevant to firm financial performance when also factoring in the many other predictors, a conclusion that is contrary to the findings of King, Srivastav, and Williams (2016), who posit that CEOs with MBAs outperform their peers. Bhagat, Bolton, and Subramanian (2010) also conclude that CEO education does not significantly impact long-term company performance, although this research only partially supports the assertion of Bhagat and colleagues (2010) that the education level of a new CEO is significantly related to the level of the CEO being replaced. When considered along with previous research, this current study's findings indicate that while CEO education may have an influence on the skills, behaviors, and decision-making of the CEO, the education of CEO candidates should not be a primary determinant of employment and does not ultimately impact the performance of the organization.

The findings from this current study indicate that investment analyst downgrades do not impact firm performance significantly and are not significantly related to other predictor variables. Wiersema and Zhang (2011) note that the downgrading of the stock of investment analysts increases the likelihood of CEO dismissal because boards strive for shareholder gains through stock market performance. This contradiction highlights the importance of the distinction between *internal* performance (ex. change in free cash flow) and *external* performance (ex. stock market performance). Agency theory would argue that stakeholders such as employees and vendors would value internal performance more, given that such performance ensures stability and reliability of desired outcomes. Conversely, shareholders generally value stock market performance more.

Whereas this research has firm performance as the outcome, the finding that investment analyst downgrades are not significant is compelling. It shines a light on the challenge faced by board of directors to ensure long-term stability by focusing on increasing firm performance while maximizing shareholder returns—two objectives that are not always in harmony. A more significant issue is raised here as well. Christensen (2012) points out that in the 1960s, the average holding period for stocks was 6 years; in 2012, 40% of trading volume was managed by hedge funds with an average holding period of 60 days, and 55% of trading volume was managed by mutual and pension funds with an average holding of 10 months. This means that some 95% of trading volume is executed by traders who do not hold the shares for even a year. Yet, research such as that by Wiersema and Zhang (2011) and many others continue to ignore those who have a vested interest in the long-term health and performance of the firm.

While board size is shown here to have a significant impact, supporting previous research (Schepker et al., 2018), the presence of the CEO on the board is not nearly as critical as is often thought. Davidson III, Nemec, and Worrell (2001) previously argued that CEO duality (the CEO is also the Chair of the Board) creates a positive market reaction, inconsistent with the previously stated agency theory. This current research presents an example of firm performance (*internal* performance) being unaffected by a phenomenon that evidently results in a positive *external* performance (market reaction).

The findings of this current study also achieve a greater level of robustness and reliability from a sample size significantly greater than that used by Davidson III et al. (2001). In practice, decision-makers should consider whether the long-term financial well-being of the firm takes priority over short-term shareholder sentiment—outcomes which are often misaligned.

Jalal and Prezas (2012) suggest that large firms require more managerial skills and experience, while Hamori and Koyuncu (2015) find that previous CEO experience is negatively associated with post-succession performance. However, both analysis types used in this current research fail to indicate statistical significance of previous CEO experience as being indicative of future firm performance. Previous CEO experience is a moot point at best. It should not be a primary qualifying characteristic unless a specific firm's circumstances and a candidate's other qualifications resultant of previous CEO experience indicate an ideal fit.

Industry and firm financial metrics have a critical impact and merit inclusion in models, even as focal explanatory variables. Jalal and Prezas (2012) relegate firm size, or natural log of assets, to a firm-level control variable. Rivolta (2018) designates firm size, pre-succession income, and pre-succession ROA as descriptive and not explanatory variables. An agency theory perspective is common in leadership and strategy research, and strategy research often utilizes performance measures as outcomes (dependent variables). Therefore, it stands to reason that examining the role of CEOs, as well as the various related areas of potential research, could benefit from the inclusion of additional robust quantitative explanatory variables such as standard deviation of equity, pre-succession ROA, and the natural log of assets in models, such as the cross-disciplinary research by Parrino (1997) that explored firm size and CEO selection from a financial economics perspective. In practice, those evaluating the performance of a CEO should also place a greater emphasis on industry metrics in addition to firm financial metrics beyond the standard figures reported in typical financial reports.

CEO age has been explored in a variety of contexts. Chowdhury and Fink (2017) and Serfling (2014) each find that older CEOs engage in less risk-taking behavior such as investing more in research and development; thus, CEO age is determined to be negatively related to firm performance. In response to those examples, this current study finds that outgoing CEO age is significantly positively related to long-term future firm performance, suggesting that the steadying hand of the experienced incumbent CEO serves to leave the firm in a position to realize significant growth in the future. This could be due to a variety of factors, such as the older incumbent CEO's stewardship attributes (Davis et al., 1997), vision and leadership (Nelson, 2003), or more mature external networks (Aldrich, Rosen, & Woodward, 1987; Hansen, 1995; Lee & Tsang, 2001). This research also supports lower ages for incoming CEOs.

The tenure of the incumbent CEO has an interesting effect on firm performance. This current study provides additional support to previous research, ranking tenure as a critical factor in post-succession firm performance. For example, Guthrie and Datta (1997) found a positive association between firm size and CEO tenure, possibly suggesting organizational conservatism, which leads larger, more complex organizations to hire older CEOs and retain CEOs longer in order to maintain organizational familiarity. In their comprehensive review of succession literature, Berns and Klarner (2017) found that firm size strongly influences CEO succession, and Finkelstein, Hambrick, and Cannella (2009) show that larger firms significantly affect CEO succession rate.

Founders have a moderate impact on succession. Wasserman (2003) previously showed that founders are less likely to be replaced, even amidst poor firm performance. As organizations mature under the leadership of a founder, it is essential that other stakeholders and shareholders, such as boards of directors or investors, evaluating executive performance must be free of bias that favors a founder.

Previous researchers have examined the benefit of designating an heir apparent. While opting to hire an outside CEO may benefit an organization by increasing the likelihood of change within the organization (Berns & Klarner, 2017), prior research about the effect of heir apparent successions consistently focuses on the relationship between heir apparent successions and shareholder returns. Harris and Helfat (1998) indicate that negative returns occur when an heir apparent is not designated. Other studies also focus on shareholder value, suggesting a positive relationship between heir apparent designations and shareholder returns (Behn, Dawley, Riley, & Yang, 2005; Shen & Canalla, 2003; Zhang & Rajagopalan, 2004). This current study ignores shareholder value to focus on the performance of the firm, which recontextualization results in a reduced prioritization of heir apparent designation in comparison with other succession predictors, concluding that future firm financial performance is impacted less by having a designated heir apparent than previously believed.

Limitations and Future Research

As with any research, there are multiple potential limitations to this study. The first limitation of this research is the sample size. Given the number of variables analyzed herein, conventional wisdom suggests that a sample size of 300 to 470 successions could result in more meaningful traditional regression analysis. Additionally, while the data included in this study is from various secondary sources, primary data would enrich the research by ensuring the validity and accuracy of information. Primary data could also provide an added layer of insight as well, potentially including variables of interest such as the decision-making processes and perceptions of CEOs, members of boards of directors, and other stakeholders. Other primary data, such as transcriptions of succession announcements, relevant board meetings, and company financials, could further enhance analyzable data and open new areas of research.

Future researchers can explore some of the newly identified interactions between predictor variables or among or within categories of predictors. For example, an exploration of the theoretical basis of the significance of lead time in succession is poised to become a significant stream of research. Furthermore, future researchers could utilize "control firms" such as organizations not undergoing successions to explore the effects of many of the predictors presented here with their impact on firms not experiencing a CEO change.

Finally, a broader application of machine learning should be explored in the areas of strategy and management research. Given the impact machine learning has had in so many other areas, there is little doubt that machine learning can contribute significantly to advancing such research.

Conclusions

This study serves to advance towards a more precise and comparative assessment of the factors that lead to a change in leadership, building upon and clarifying extant research regarding the many factors that have been shown individually to impact firm performance significantly. This research is helpful both to a board of directors and a CEO who is contemplating stepping down. Extending beyond the grounding theories, utilizing a machine learning approach will help organizations less awkwardly address the elephant in the room when considering a change in CEO, being empowered by unbiased and robust data. Furthermore, while this research has pragmatic application by providing empirical support to organizations seeking to prepare for a CEO change, the findings from this study also lays the groundwork for the analysis of promotion and succession events for other top management and middle management roles.

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VITA

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