

DIGITAL TRANSFORMATION: HOW TO BEAT
THE HIGH FAILURE RATE

By

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Abstract: Firms every year spend \$1.3 trillion on digital transformation programs to improve efficiency because digital leaders outperform their peers in nearly every industry. However, digital transformations that are intended to improve efficiency (e.g., ERP, CRM, Analytics, etc.) have a high failure rate (up to 90%), resulting in adverse impact to firms' operations and intent to further innovate. While extant research talks about the importance of vision, management, and culture as critical success factors, even digital transformations within the same firm often fail to achieve similar results. Based on Diffusion of Innovation theory and data from three digital transformation programs within a firm that achieved vastly different results, I posit five factors as key influencers of digital transformation success: a) Innovation Attributes, b) Opinion Leaders, c) Diffusion Approach, d) Timing, and e) Duration. I also use machine learning (ML) techniques such as leave-one-out-cross-validation (LOOCV) to show the superiority of ML over regression to determine feature importance. In addition to contributing to theory, this research will help practitioners increase the success rate of future digital transformations.

In the first chapter, I introduce the reader to digital transformation, why firms want to digitally transform, and the high failure rate these firms face when they embark on digital transformation. In the second chapter, I perform a literature review of key digital transformation research performed to date and define the underlying theory and the factors used in this study. In the third chapter, I describe the research design and its appropriateness for studying the research question. In the fourth chapter, I perform hypothesis testing with sample data from three studies to test whether the five factors significantly influence digital transformation outcome. In the sixth chapter, I use the machine learning technique LOOCV to determine feature importance. Finally, in the last chapter I describe the key research contributions of this research and future directions.

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CHAPTER I

INTRODUCTION

Situating the Research Problem

Digital Transformation is the application of digital capabilities to processes, products, and assets to improve efficiency, enhance customer value, manage risk, and uncover new monetization opportunities (Rizzo, 2017). Today more than ever, incumbent firms in industries such as retail, telecom, banking, etc. are being forced to change due to disruption by new and innovative competitors (Geissinger, Laurell, & Sandström, 2018). One way to respond to such disruption is to digitally transform.

There are broadly two types of digital transformations, the ones that are performed to achieve *top line growth* by identifying new monetization opportunities (new products, new channels, new markets, etc.) and the others to achieve *bottom line savings* in terms of efficiency improvements (process changes, automation, newer technology, etc.). The focus of this study is digital transformations that are performed to achieve bottom line savings through efficiency improvements. Starbucks' mobile app reduced 10 seconds from each transaction and 900,000 hours of customer wait time annually to order coffee.

Starbucks processed 3 million mobile transactions every week through this app in 2013, allowing customers to order and pay faster and in the process serving more customers (Fitzgerald, Kruschwitz, Bonnet, & Welch 2014). Another example is Nestle USA's Enterprise Resource Planning (ERP) solution that increased the accuracy of demand planning for its products across

many of its brands, resulting in making the right products at the right quantity and enabling a \$325 million savings across the enterprise (Glick, 2001; Dieringer, 2004).

Not all firms are digitally transforming to improve efficiency, and hence we will consider firm management statements as a basis for whether a digital transformation was recently performed at the firm. Researchers have not yet been able to agree on an exact definition of a successful or failed digital transformation. Thus in the context of digital transformations intended to improve bottom line savings, we will use feedback from the users, project teams, and executives at the firms to determine whether a digital transformation was perceived as a success or a failure.

An example of a successful digital transformation to improve efficiency would be LG's implementation of a central human resource management system (HRMS) for its 82,000 employees in 39 countries. As per Mi Jung Kang, Chief Human Resources Officer for LG, the HRMS system helped LG to standardize HR processes across different regions and gain significant cost savings and efficiency improvements (Seth, 2018). Another example of a successful digital transformation to improve efficiency is Fuze Energy Drink's ERP implementation, which allowed it to scale rapidly as the company went through rapid growth. The digital transformation helped Fuze improve inventory management and financial transparency and helped balance its supply and demand during a phase of rapid growth (Seth, 2018).

An example of a failed digital transformation would be Vodafone's rolling out of its customer relationship management (CRM) mobile billing system that resulted in a flood of customer complaints ranging from incorrect charges to customers being charged even after they cancelled their contracts. This resulted in an investigation by regulators, and Vodafone was fined £4.6M and experienced a subsequent £54M loss in sales during the quarter when the system was rolled out (Lauchlan, 2016; Kollwe, 2016). Another example of a failed digital transformation is HP's rollout of an order processing and supply chain system that resulted in lost orders and cancellations from customers due to delays resulting in a \$400M impact on HP (Thibodeau & Tennant, 2004).

There are several such examples of firms that have struggled to digitally transform; as de Los Reyes (2015) states, the failure rate is 70% or higher when it comes to digital transformation. While extant literature talks about how successful firms that have been around for a long time ruthlessly transform without worrying about their legacy or core expertise, it does not explain why other firms cannot replicate this process, often within the same industry and sometimes with more resources (Clemons & Hann, 1999; Johnson, Yip, & Hansmans, 2012).

While the role of technology (Weber & Monge, 2017; Sheppard, 2017), firm culture (Nag, Corley, & Gioia, 2007), equilibrium (Miller, 1992) and management (Hornsby, Kuratko, & Zahra, 2002; Zook, 2007; Teece, Pisano, & Shuen, 1997) has been studied in extant literature, current knowledge has not helped in reducing the 70% or higher failure rate of digital transformations. So the research problem that we are looking to solve is how to increase the success rate of digital transformations.

The scope of the problem involves key aspects that can improve digital transformation success. Its depth includes different levels of stakeholders (owners and agents) that participate in the transformation. Its breadth includes the extent to which the firm intends to transform. It could be one or more strategy, such as newer processes, automation, technology upgrades, etc. The length the problem to be studied would be through the duration of digital transformation and for the next few months thereafter.

Grounding the Research Problem

To address journalists' questions as shown in Table 1, the problem of digital transformation success is of importance to managers who are responsible for improving efficiency. A failure of transformation may not always result in firm failure, but it usually results in monetary losses and harm to the firm's reputation (Lauchlan, 2016; Kollwe, 2016; Thibodeau & Tennant, 2004). Hence, this research problem of improving digital transformation success is not only important to managers responsible for efficiency improvements, but also has a broader impact on firm standing with customers, regulators, employees, etc.

Table 1: Journalists Enquiries Mapped to Research Question

Journalist & Article Description	Symptoms	Diagnosis and Mapped to Research Questions
<p>Boulton (2018). <i>Twelve Reasons Why Digital Transformations Fail</i></p>	<p><i>“Leadership of digital transformations is in crisis, with CEOs failing to shepherd or back a coherent strategy”</i></p>	<p>Opinion leaders and innovation attributes</p>
	<p><i>“Digital transformation efforts are coming up short in part because digital transformation is as much a leadership issue as it is a strategy, technology, culture and talent issue.”</i></p>	
	<p><i>“Resistance to change can grind transformations to a halt.”</i></p>	<p>Diffusion approach and innovation attributes</p>
	<p><i>“The snail’s pace isn’t helping. Only 4 percent of respondents said they realized half of their digital investment in under one year, with the majority of respondents saying it has taken their company two to three years”</i></p>	<p>Duration</p>
<p>Sweeney (2018). <i>Lessons Learned from Failed Digital Transformations</i></p>	<p><i>“Many factors, like the economy or product appeal, can affect a company’s success with digital transformation”</i></p>	<p>Innovation attributes and timing</p>
	<p><i>“Digital is a multi-faceted, diffuse approach that involves more than just technology.”</i></p>	<p>Diffusion approach and innovation attributes</p>
	<p><i>“The appeal of digital and new technology shouldn’t consume or overtake existing systems”</i></p>	<p>Duration</p>
	<p><i>“Digital transformation are an ongoing process that includes continuous monitoring and intervention from digital and non-digital leaders”</i></p>	<p>Opinion leaders</p>
<p>Westerman (2018). <i>Why So Many High Profile Digital Transformations Fail?</i></p>	<p><i>“Digital bets did not pay off quickly enough, or richly enough, to counter the drain they represented on the rest of the business.”</i></p>	<p>Duration and timing</p>
	<p><i>“The allure of digital can become all-consuming, causing executives to pay too much attention to the new and not enough to the old.”</i></p>	
	<p><i>“Economy or the desirability of your products, that can affect a company’s success as much or more than its digital capabilities”</i></p> <p><i>“When things are not going so well in the existing business, the call of a new business model can become more powerful than it should.”</i></p>	<p>Innovation attributes and timing</p>
	<p><i>“Digital is not just a thing that you can buy and plug into the organization. It is multi-faceted and diffuse, and doesn’t just involve technology.”</i></p>	<p>Diffusion approach</p>
	<p><i>“Jeff Immelt — a powerful advocate of the company’s digital ambition.”</i></p>	<p>Opinion leaders</p>

To more closely describe the problem, firms that failed to achieve digital transformation success are numerous and have suffered financial losses and reputational damage (Lauchlan, 2016; Kollwe, 2016; Thibodeau & Tennant, 2004). Digital transformation to improve efficiency as evidenced by these examples is not limited to a certain industry, but spans a broad range of industries. On the contrary, several firms such as Starbucks, LG, Fuze Energy Drinks, etc. achieved digital transformation success resulting in significant efficiency improvements and increased revenues and profits.

Rapidly changing technology threatens firms and industries, putting a squeeze on revenues and requiring firms to improve efficiency and lower costs (Abbosh, Nunes, Savic & Moore, 2017; Sheppard, 2017). Digitally transforming is one way a firm can compete in this environment (Christensen, Bartman, & Van Bever 2016; Carayannis, Sandakis, & Walter 2015; Zook, 2007). Leslie (2015) shows that the key to enduring growth is digital transformation. However, achieving successful digital transformation remains elusive with 70% or more firms failing in the process (de Los Reyes, 2015; Johnson et al., 2012; Clemens & Hann, 1999). Thus, improving digital transformation success is an important issue.

Diagnosing the Research Problem

The problem of improving digital transformation success is complicated and may not have one single answer; a single study may not address it all. However, during the interviews that I conducted with respondents in the field who have performed both successful and failed digital transformations, certain symptoms were common among the successful digital transformations that seemed to be missing in the failed digital transformations. In addition to the right strategy, successful digital transformations seemed to also have these five common factors: 1) innovation attributes, 2) opinion leaders, 3) diffusion approach, 4) timing, and 5) duration.

Innovation attributes are characteristics of an innovation, such as: a) relative advantage, b) compatibility, c) complexity, d) trialability, and e) observability (Rogers, 1963). Relative advantage is how users perceive the innovation in comparison to previous ideas. Compatibility is how

users perceive the innovation fits into their present habits and routines. Complexity is users' perceptions on how easy or difficult it is to use the innovation. Trialability is the ability to try the innovation before committing to it. Observability is the extent to which the benefits of an innovation are visible to future users.

Opinion leaders are members in a team who have the greatest influence on other team members' adoption of an innovation in the diffusion process of innovation (Cho, Hwang, & Lee, 2012).

Research studies related to innovation adoption shows that followers adapted three times faster to an innovation when their opinion leaders introduced them to it (Hao, Padman, & Telang 2011; Seebauer, 2015; Brown, Chen, & O'Donnell 2017). During interviews, several respondents attributed to opinion leaders the success of the digital transformation. Interestingly, a few of the respondents also discussed the lack of opinion leaders as a cause for the failure of the digital transformation.

The diffusion approach states that innovators (first 2.5% of adopters) and early adopters (13.5%) are attracted when communications contain words such as "be the first." Once the 16% adoption rate is achieved, communication style must be switched to say "join the 1000s," to attract the early majority (36%) and the late majority (36%) adopters (Rogers, 1963). When firms practice this style of communication, the innovation diffusion is faster (Maloney, 2010). This approach has been shown to work in other innovations contexts and to change habits (Lee, Ho, & Wu, 2018; Augustine, Glassman, Harmening, Meabon, & Opp, 2015). Few of the respondents attributed the success of their digital transformations to pursuing this type of a change management strategy where communications were tailored based on leadership and team members' personalities.

Timing is when a firm decides to start an innovation (Schoenecker & Cooper, 1998). Research studies have shown that timing plays a critical role in success of a strategy in various contexts such as - entering a new industry (Whipp, Adam, & Sabelis, 2002); new policy (Granqvist & Gustaffson, 2016); and new technology (Leng, Lui, Tan, & Pang, 2015; Brueller, Ellis, Segay, & Carmeli, 2015). Several respondents raised the issue of timing during interviews and attributed the outcome of digital transformation on when the firm decided to pursue it.

Duration is the time between the start and end of a digital transformation initiative. In their research, Wisse and Sleebos (2016) show a relationship between long duration and fatigue due to high levels of uncertainty, demanding work schedules, and significant pressure on team members to deliver under pressing circumstances. Other studies show that prolonged fatigue results in poor job performance (Feddock, Hoellein, Wilson, Caudill, & Griffith, 2007), burnout (Demerouti, Bakker, & Leiter, 2014) and turnover (Levenson, 2017). These are some of the topics brought up by respondents as impacting digital transformation success.

Importance of the Research Problem

Digital transformation success is important for firms because digital leaders outperform laggards in key financial measures. In a study of 344 firms over three years with median revenue of \$3.4 billion, digital leaders outperformed laggards on gross margin, operating margin, and profit margin (Bock, Iansiti, & Lakhani, 2017). In another study of 400 companies over two years, Westerman, Tannou, Bonnet, Farraris, & McAfee (2012) show that firms that are successful in their digital transformations outperform their peers in every industry, which again shows the importance of digital transformation success.

Heller Baird and Gonzalez-Wertz (2011) conclude that in the future success of firms largely depends on the degree to which they master digital capabilities and that it is important for firms to seamlessly integrate their digital components with physical operations to successfully transform their business models (Berman, 2012). However, 84% of companies fail to digitally transform (Rogers, 2016). Zobell (2018) reported how firms lose \$900 billion every year due to digital transformation failures. An example is the Waste Management failure of their ERP system, resulting in severe disruption to their operations and a lawsuit filed against the software provider (Kanaracus, 2008). Another example is the failure of the Vodafone CRM system resulting in incorrect bills being sent to customers and in a £4.6M fine and a £54M loss in market share (Lauchlan, 2016).

In a survey of 450 chief information officers, chief technical officers, and chief digital officers, a majority of the respondents agreed on the importance of digital transformation for the future success

of their firms, but expressed how 90% of these digital transformations continue to fail (Carey, 2017). According to the U.S. Government Accountability Office, the Navy spent about \$1B on four pilot digital transformation programs but failed in the process (Songini, 2005). Similar issues with digital transformation failures affected the rollout of the Affordable Care Act in 2009 when millions of people could not enroll online, resulting in a delay in enrolling in health insurance coverage.

Fitzgerald et al. (2014) hence say that firms routinely invest in technology but too often get routine results. So our research problem of how to reduce the high failure rate (70%-90%) in digital transformations is important and unaddressed. Despite the existing knowledge of management, culture, and vision being key factors influencing digital transformation success, even within the same firms sometimes certain digital transformations succeed and others fail. One exception to these studies is the meta-analysis by Allen et al. (2017) of 76 studies between 1973-2013 showing diffusion of innovation (new policies, programs, and practices), almost half in healthcare settings, investigating the latent construct of “inner setting” within organizations. The two most frequently assessed constructs were organizational climate and readiness for implementation. Less than half of the articles reported influence of firm-level characteristics on diffusion of innovation.

Our research advances the Allen et al. (2017) meta-analysis finding of an important gap in determining why firms continue to fail at certain digital transformation programs and manage to succeed at others despite the same management, culture, and vision. I hope to provide important insights into the necessary factors for digital transformation programs to consistently succeed.

Selecting the Research Question

The part of the problem that merits research attention and focus is the factors that significantly increase digital transformation success. Based on respondent interviews, diagnosis of the research problem, and literature reviews, the following are the research questions that I plan to investigate.

- Do innovation attributes significantly influence the degree of success of digital transformations?
- Do opinion leaders significantly influence the degree of success of digital transformations?

- Does following a diffusion approach significantly influence the degree of success for digital transformations compared to changes in management alone?
- Does the timing of digital transformation significantly influence the degree of success?
- Does the duration of digital transformation significantly influence the degree of success?

The reason I selected these five factors (innovation attributes, opinion leaders, diffusion approach, timing, and duration) was that they came up very often during the interviews that I conducted with practitioners in the field who have performed multiple successful and failed digital transformations. A literature review of extant research also shows that very little research has been done on these factors within the context of digital transformations, and even fewer in the specific case of digital transformations that are performed to improve efficiency and hence warrant further investigation.

My research question aims to permit and entertain at least two plausible answers as to whether innovation attributes, opinion leaders, diffusion approach, timing, and duration significantly influence digital transformation success. It is possible that some of these factors may not be significant at all, some may be significant and others may not be, some may be less effective than others in determining digital transformation success.

Therefore the answer to my research question solves a key part of the problem from managements' perspective: what are factors that they should focus on to significantly influence digital transformation success, specifically in the context of programs that improve efficiency. This should substantially improve the situation for managers that are performing digital transformation today by providing them specific variables that can significantly increase their success. Additionally, my research question also increases knowledge and competence of the managers performing digital transformation.

CHAPTER II

REVIEW OF LITERATURE

Conceiving the Theory

In my research, I'm using a *Model Theoretic* perspective where empirical research does not confirm or refute a theory but we use it to improve the theory (Harris, Johnson, & Souder, 2013). To understand whether I have the right problem, I discussed it with multiple respondents who acknowledged the importance of understanding how innovation attributes, opinion leaders, diffusion approaches, duration, and timing influence digital transformation success and the need for this type of practitioner-focused research.

One of the respondents was a digital transformation expert who led a large multiyear initiative to standardize key business processes in a group of globally dispersed firms that were acquired by the parent firm. The initiative was rated to be very successful by the executive leadership and was reflected in the stock price of the firm during and after the digital transformation. The respondent attributed the success to: 1) how users perceived the innovation attributes and compared them to the previous solutions with which they were familiar, 2) the presence of a few key opinion leaders who brought their respective followers along, 3) following a diffusion approach to attract innovators and early adopters initially who then brought over the early majority and late majority of employees, 4) the timing of the initiative when the firm was in its growth phase where there was less pressure to produce immediate results, and 5) a specific duration with some predefined milestones to show how the digital transformation was progressing

Another respondent was also a digital transformation expert who had recently led a large ERP program for a newly created firm that was carved out of a large corporation. The digital transformation program was not successful; the respondent attributed this to: a) the perception of the users that the solution was not flexible and might not be well suited for the firm's needs, b) a lack of opinion leaders within the firm, c) the change management team did not have a coherent plan to attract project team members, and d) bad timing since the firm was still in its early stages and did not have the structure for such a digital transformation.

There were several other respondents that I interviewed during this step of conceiving my theory. A majority of the informants thought that the digital transformations of which they were a part were unsuccessful, which was consistent with the 84% failure rate of digital transformations (Rogers, 2016; de Los Reyes, 2015). This is a good indication that our research has low common method bias. a majority of the respondents also focused on innovation attributes, opinion leaders, diffusion approaches, duration, and timing as the key factors that may have impacted digital transformation success.

Theoretical Model and Hypotheses

Diffusion of Innovation Theory (DOIT) indicates that innovations that diffuse typically have four key characteristics: a) perceived innovation attributes (relative advantage, compatibility, simplicity, observability, and trialability); b) communication channels for the innovation to be communicated to its wider audience; c) time (when the decision is made to adopt or reject the innovation); and d) social system, such as environment, beliefs, societal factors, etc. of the users (Rogers, 1963).

According to Rogers (1963), innovation attributes play a key role in adoption. Relative advantage occurs when an innovation is perceived to be superior to what it supersedes. Compatibility is how consistent the users perceive the innovation is with their current values, habits, and past experiences. Simplicity is the perception of the user of how easy it is to use this innovation. Trialability is the

ability of the innovation to be tried out first on a limited basis before committing to its broad use.

Observability is the ability of the innovation and its results to be noticed and communicated to others.

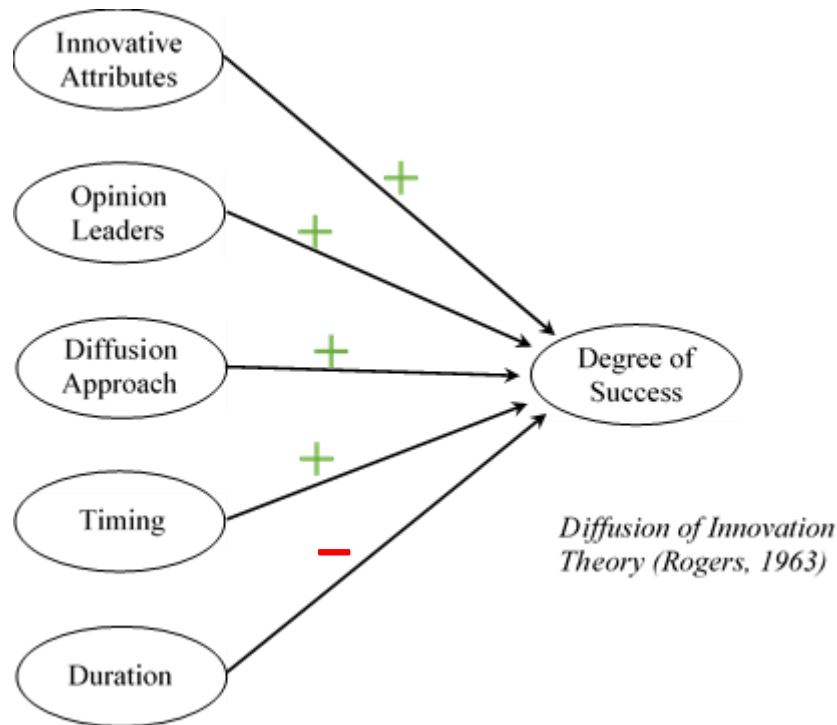


Figure 1: Theoretical Model

In the Rogers (1964) DOIT, communication channels are the medium used to spread the word for the innovations to diffuse. As shown in Figure 2, there are two communication channel models: the Hypodermic Needle Model and the Two-Step Flow Model using opinion leaders. In the Hypodermic Needle Model, communication from mass media directly reaches the end users. In a Two-Step Flow of Communication Model, information flows to the opinion leader who then give the information to lesser active members of their group.

The opinion leader exerts a great deal of influence on his group and is trusted by his followers, so there is a higher adoption of information (Katz & Lazarsfeld, 1955). The influence of the opinion leader is, however, limited to his group; the opinion leader does not influence followers in other groups. An example of this theory in practice might be a political leader who exerts a great deal of

influence on his followers but whose influence diminishes outside his group. I posit that the existence of opinion leaders across different functions within the firm increases the adoption of digital transformation by their respective followers, thereby improving digital transformation success.

In the Diffusion Approach, innovation adoption follows a Bell curve as shown in Figure 3. The first 2.5% of users are the innovators; the next 13.5% are called the early adopters followed by early majority (34%), late majority (34%); the last 16% are called the laggards. Maloney’s (2010) 16% Rule talks about how communications must be tailored for innovations to diffuse. To attract the first 16%, the adoption messaging should highlight “scarcity” by saying “Be one of the first.” for the next 68% early majority and late majority), the communication has to be switched to “social proof” by saying “Join the 1000s”

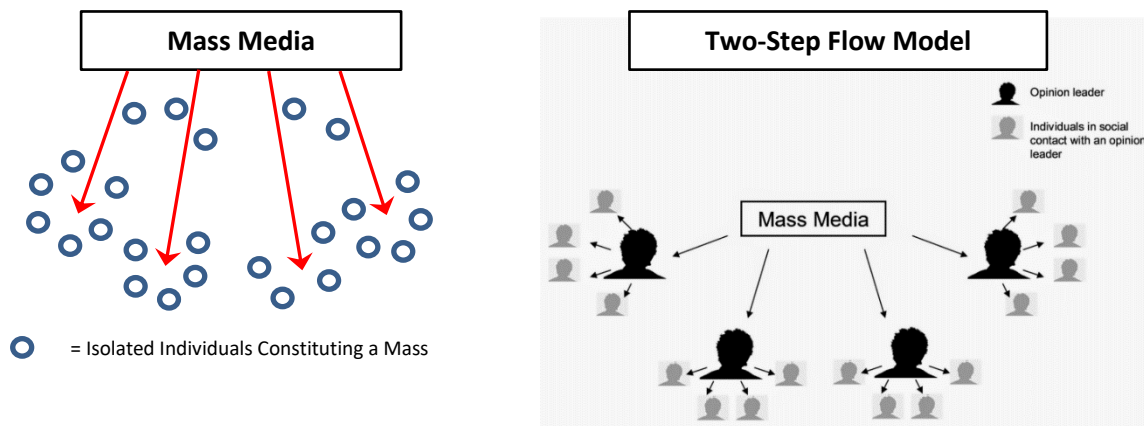


Figure 2: Hypodermic Needle Model (Left) and Two-Step Flow Model (Right)



Figure 3: Bell Curve for Innovation Adoption (Rogers, 1963)

According to DOIT, time and social system often explain why a certain innovation was successful in one culture and failed in another. While time is when the innovation decision to adopt or reject is made, social system is the environment, culture, values, and beliefs of the user that influence adoption of an innovation. In our context of the digital transformation, timing of when the firm starts its digital transformation (startup phase, growth phase, peak phase, decline phase, and going out of business phase) includes key elements of time and social system.

Another time and social element of DOIT is duration of the digital transformation. Duration is the time period between the start and the end of the digital transformation and may be another factor that negatively effects innovation adoption. I argue that digital transformations that go on for a long duration of time are impacted by factors outside the control of the program, such as economic crises, firm-level crises, and fatigue. I will test this during my research by investigating whether duration has any impact on the outcome.

Innovation Attributes

In a meta-analysis of 75 articles to study the influence of innovation attributes on adoption, Tornatzky & Klein (1982) conclude that compatibility, relative advantage, and complexity are the greatest influencers out of the five characteristics. A more recent study of adoption of sharing economy (Example: Uber, AirBnB, Lyft, etc.) also shows the importance of innovation attributes (relative advantage, compatibility, complexity, trialability, and observability) on perceived usefulness and ease of use (Min, So, & Jeong, 2018).

In a pre-test/post-test experimental study at a hospital, a disease management system initially had a 33% adoption rate. When DOIT's innovation attributes were applied to redesigning the system, the adoption rate jumped to 100% (Hu et al., 2018). In another meta-analysis of key innovation attributes that effect innovation adoption, Arts, Frambach, and Bijmolt (2011) show that while consumers may show a desire to adopt to complex innovations that better match their needs, they actually adopt with less complexity and higher relative advantages from the previous idea. Also, in two studies to evaluate whether personal characteristics and innovation attributes have any effect on innovation

adoption, innovation attributes seemed to be the only factors that effected adoption; personal characteristics such as race, age, religion, etc. had no effect (Ostlund, 1974).

In his study, Al-Gahtani (2003) shows that the five attributes of innovation (relative advantage, compatibility, complexity, trialability, and observability) explains up to 87% of the innovation rate of adoption. Hence, I posit that perceived innovation attributes have a positive effect on the degree of success of digital transformation.

H₁: Perceived innovation attributes have a positive effect on the degree of success of the digital transformation.

Opinion Leaders

Opinion leaders are members of a team who have the greatest influence on other team members' adoption of an innovation in the diffusion process of innovation (Cho et al., 2012). Hao et al. (2011) study the adoption of a mobile clinical IT system, similar to a digital transformation, in a healthcare setting. Physicians under the influence of an opinion leader were three times more likely to adopt this new technology. Researchers also conclude that incentivizing a small number of opinion leaders to adopt a new technology is effective in diffusing new technology to their followers.

In a longitudinal study of adoption of e-bikes and e-scooters, 1,398 e-bikers and 133 e-scooter owners were studied for over a year. The researchers noticed that while the influence of opinion leaders on peers was small, it was effective when opinion leaders were provided relevant product information and other supporting policies (Seebauer, 2015). Using a two-step flow of communication theory, Turnbull and Meenaghan (1980) also discuss the notion that opinion leaders can influence their followers to adopt a new innovation through diffusion whereby the innovation or a new idea or practice spreads through a social system over time.

Valente and Davis (1999) also show the importance of interpersonal networks and the role of opinion leaders with innovation diffusion. They describe how opinion leaders are selected in five different ways: a) some individuals select themselves to be peer leaders; b) program staff or project teams select the leaders; c) community members recruit participants, not leaders, and they in turn

each recruit new participants; d) some selected individuals in a community nominate others to be leaders; and e) all community members are invited to nominate opinion leaders.

Liu, Sidhu, Beacom, and Valente (2017) also show the role of Social Network Theory to explain the relationship between opinion leaders and followers considering a high degree of centrality, a high degree of closeness, and high betweenness centrality. Theory of Weak Ties can also be used to explain diffusion of innovation through opinion leaders, for example, finding a new job through someone with weak ties instead of friends or family (Granovetter, 1983).

The Brown et al. (2017) research highlights the importance of recognizing and enabling opinion leaders whose opinions are sought by their peers. For successful adoption of innovation, since opinion leaders influence attitudes and perceptions of other organization members, firms should encourage and guide opinion leaders so they can help drive their followers to positive organizational outcomes. Hence I posit that opinion leaders within a firm have a significant positive effect on digital transformation success.

H₂: The degree to which opinion leaders within the firm are involved in the digital transformation is positively associated with its success.

Diffusion Approach

Maloney's (2011) 16% Rule of innovation diffusion states that innovators (2.5%) and early adopters (13.5%) are attracted when communications contain words such as "be the first." Once the 16% adoption rate is achieved, communication style must be switched to say "Join the thousands," to attract the early majority (36%) and the late majority (36%) adopters. When firms practice this style of communication, the innovation diffusion is faster and firms can cross the chasm (16%) when the early majority and late majority adopt the innovation, in this case digital transformation, and make it successful.

Lee et al. (2018) support this in their study of new technologies where the initial communication focus was on form and functional newness to attract the innovators and early adopters. Once the 16% adoption rate was achieved, the opinion leaders influenced their peers, resulting in faster diffusion of

innovation within the firm. Augustine et al. (2015) similarly show the transformation of 596 universities to a tobacco-free campuses. The adoption of this transformation was consistent with Rogers' (1963) Diffusion of Innovation Theory where innovators and early adopter campuses were able to diffuse this transformation and bring the early majority and late majority campuses on board.

Based on this research, I posit that digital transformations that use two-step adoption messaging attracting first the innovators and early adopters within the firm (16%) by saying "Be the first to lead the digital transformation" and then switching the communication strategy to attract the early majority and late majority (72%) by saying "Join the thousands who have digitally transformed" will have a significant positive effect on the degree of success of the digital transformation program.

H₃: Digital transformations that rely on a diffusion approach are more successful than those that rely on change management alone.

Timing

Timing in general has not been of major interest in transformation literature until Schoenecker & Cooper (1998) showed how timing influences strategic transformation of a firm into new industries and a strong first mover advantage increased success. Whipp et al. (2002) then talked about Kaiology (Greek term for the right time to do something) and its influence on transformation outcome. More recently, Granqvist and Gustaffson (2016) show how successful leaders use timing as a key influencer to bring about changes in institutions. Leng et al. (2015) in their study of 360 technology firms conclude that timing plays an important role in success.

Gilbert and Birnbaum-More (1996) show that firms can gain competitive advantage by using optimal timing to introduce their digital transformations. There are three main aspects to innovation timing that ultimately affects innovation success: *now*, *never*, or *sometime in the future* (Mann, 2005; Kuckertz & Wagner, 2010). Some digital transformations are time sensitive and must be adopted *now* to realize their benefits, such as e-commerce, EDI, mobility, etc. Some innovations must be adopted *sometime in the future* as the alternative costs would be higher and adversely impact the firm's

competitiveness. These could be digital innovations such as cloud computing, laptop technology, virtualization, etc. (Kim, 2011; Low, Chen, & Wu, 2011).

Finally, some digital transformations may *never* be adopted given the cost constraints or switching challenges, such as ERP, CRM, automation systems, etc. (Mezghani, 2014; Hossain, 2001). Industry adoption of similar innovation also indicates an *optimal timing* for introducing this digital transformation within a firm and improves its odds of success due to the availability of talent in the market and vendors with sufficient expertise. In a study of 181 firms on EDI adoption, competitive pressure was identified as one of the key factors that influenced innovation adoption (Premkumar, Ramamurthy, & Crum, 1997; Crum, Premkumar, & Ramamurthy, 1996; Patterson, Grimm, & Corsi, 2003).

Based on this research, I posit that innovation timing has a positive influence on digital transformation success with firms that adopt newer innovations at the optimal time being able to capture the benefits of such innovation.

H₄: Innovation timing is positively associated with the success of a digital transformation program.

Duration

Duration is how long a digital transformation program takes from start to finish. Longer duration programs can be impacted by factors that are outside the control of the program, such as economic crises, firm-level crises, and fatigue within the team. The Innobarometer[®] 2009 survey conducted by the European Commission shows that firms reduced their investments in innovation after the 2008 economic crisis (Archibugi et al., 2013a; Filippetti & Archibugi, 2011; Kuznetsov & Simachev, 2010). In a study of eight Latin American countries between 2008-2009, it was clear that one in four firms stopped their ongoing innovation programs due to the economic crisis (Paunov, 2012). These studies show that economic crises and other strategic crises can have an adverse impact on longer duration innovations such as digital transformation.

Extended work hour cultures today are becoming the norm with firms recruiting and reinforcing this behavior through their rewards system (Fry & Cohen, 2009). It is likely that digital transformation may involve demanding work schedules resulting in an extended work hour culture over a long duration of time, often measured in years. In their meta-analysis of several studies, Ng and Feldman (2008) show that situational demands have a strong relationship with the extended work hour cultures; the amount of hours worked had a negative relationship with all measures of employee well being and work-family conflict variables.

Studies also show that working extended hours is negatively associated with health, work performance, safety, and over-all quality of life (Lamberg, 2004; Worrall & Cooper, 1999). A study of interns over a three-month period shows that interns that felt both pressed and tired, were eight times more likely to make mistakes and four times more likely to report lack of training. High pressure and insufficient sleep over a prolonged duration were associated with poor job performance (Feddock et al., 2007).

Conway, Pompeii, Gimeno, Follis, and Roberts (2017) studied 2,000 participants over 15 years to understand what is considered to be long hours and when it impacts employee health. Results of this study show that employees who self-report working over 52 hours per week regularly report higher health-related issues compared to employees who report working 35-51 hours a week. This is one of the very few studies that have shown the relationship between number of hours worked over a long duration and the negative effects on employee health.

Scholars appear to agree that working over 50 hours per week over a prolonged duration of time, such as few months or years, is associated with negative health outcomes for employees, resulting in increased risk of injuries and health-related issues (Gilbert-Ouimet et al., 2018; Kuroda & Yamamoto, 2016; Lu et al., 2016).

Based on this research, I posit that digital transformations that are longer in duration are less successful due to fatigue. In other words, duration has a negative effect on digital transformation success with longer programs being less successful.

H₅: Duration has a negative effect on digital transformation success with longer programs being less successful.

CHAPTER III

METHODOLOGY

Statement of the Research Problem/Question

The research question that I am attempting to answer is what factors can improve the degree of digital transformation success? In my perspective, current research has failed to sufficiently address this, resulting in 90% of firms being unable to achieve digital transformation success (Carey, 2017). The *Action Science* approach (Argyris, Putnam, & Smith, 1985; Raelin, 1997) is an application of theory directly in the field with scholars and practitioners collaborating and acknowledging, rather than rejecting, the role of personal feelings within the research context. Based on this approach, I'm investigating factors such as innovation attributes, opinion leaders, the diffusion approach, timing; and duration and their impact on the degree of digital transformation success.

Research Design

This research is based on a *variance model* and predicts levels of degree of success from contemporaneous predictor variables such as innovation attributes, opinion leaders, diffusion approach, timing, and duration, as shown in Figure 1. In variance theories, the precursor (“cause”) is posited as a necessary and sufficient condition for the outcome (Markus & Robey, 1988). Variance theories thus posit an invariant relationship between causes and effects when certain conditions are met. Our conceptualization of outcomes and precursors also varies from

process theory model as our variables can take on a range of values such as 1= strongly agree to 5 = strongly disagree versus the process theory model where variables are discrete.

Data and Sample

A Qualtrics anonymous survey was emailed to participants of three digital transformation programs within the same firm. The reason for studying multiple digital transformation programs within the same firm was to keep the firm-level factors constant, including top management, culture, and vision. The reason for conducting three studies is to show that the results of the study are generalizable across multiple digital transformation programs. This approach is supported in prior research on application of diffusion theory in innovation adoption (Ostlund, 1974; Flynn, Goldsmith, & Eastman, 1996).

This sample is appropriate because a) it provides feedback from participants with experience in successful and failed digital transformations, and b) it also provides data points from multiple digital transformation programs to show reliability of results and findings. Recommended sample size was calculated for 95% confidence interval, 5% margin of error, and 50% response distribution.

As shown in Table 2, the first study was a digital transformation program that was performed to standardize business processes across acquired companies spread across the globe to improve efficiency. The sponsor, project manager and steering committee members perceived this project to be less successful. The program impacted about 3500 employees within the firm and was performed over 3 years. Key technologies used in the program were ERP, Data Warehouse, Analytics, etc. The recommended sample size was 347.

As shown in Table 2, the second study was a digital collaboration hub that was implemented in various meeting rooms using technology to improve collaboration across a globally dispersed team. The sponsor, project manager, and steering committee perceived this program to be successful. The program impacted about 220 employees, and the deployment lasted for about a year. The key technology used in this digital transformation is Microsoft's Surface Hub. Recommended sample size was 141.

Table 2: Study Sample

Type of Study	Firm	Study & Purpose	Perceived Outcome	Duration in Years	Population Size	Recommended Sample Size*
Multiple Respondent Questionnaire Survey	MNC with 21,000 employees in 30 countries	Digital Transformation Program to standardize processes	Less Successful	3.0	3,500	347
		Digital Collaboration Hub to improve meeting effectiveness	Successful	1.0	220	141
		Integrated Business Planning to improve demand/supply balancing	Failure	1.5	60	53

As shown in Table 2, the third study was an integrated business planning program that was implemented to improve demand and supply balancing, inventory optimization across global sites, and better strategic planning. The sponsor, project manager, and steering committee perceived this program as a failure due to several delays in project go-live and cost overruns. The program impacted about 60 employees, and the deployment was initially about a year but was completed in 1.5 years. Recommended sample size was 53.

Survey Instrument

Participants will respond to a multiple respondent questionnaire survey as shown in Table 3. The first series of questions, such as gender and age, help me understand the profile of survey participants. Relationship to the program helps me to understand whether the respondent was part of the project team that helped deploy this digital transformation, or a user of this digital transformation, or an executive that decided to deploy this digital transformation.

To measure innovation attributes, I use the perceived innovation attributes questions that Ostlund (1974) used in his two studies applying Diffusion of Innovation Theory to study whether a consumer would adopt or reject a consumer product. In my survey, I'm using a seven-point Likert scale (strongly agree to strongly disagree) where I ask participants their perceptions related to five key attributes of this digital transformation: 1) relative advantage, 2) compatibility, 3) complexity, 4) trialability, and 5) observability (Rogers, 1963).

To measure the presence of opinion leaders, I use the opinion leadership questions that Flynn et al. (1996) used in their five studies to measure opinion leadership and in which they concluded that the unidimensionality, reliability, and construct and criterion validity of the opinion leadership scale. In my survey, I'm using a seven-point Likert scale (strongly agree to strongly disagree) to ask respondents whether key leaders were present in this digital transformation program and whether their opinions influenced their followers to adopt the digital transformation.

To measure whether the program used the diffusion approach for innovation adoption, I use the Rogers (1963) adoption questionnaire and Maloney's (2010) 16% rule. In my survey, I'm using a seven-point Likert scale (strongly agree to strongly disagree) to measure whether the respondents agree that the digital transformation program was successful in developing a feeling of newness or scarcity among the innovators and early adopters through communications, thereby attracting this group of users (the first 16% of users) in the early stages of the program. The survey further studies whether the respondents agree that the program was able to attract the early majority and late majority of users (the next 68%) by highlighting in their communications social proof that the digital transformation worked.

To measure timing, I ask the respondents to describe the role timing played in the outcome of this digital transformation. I measure their responses on a seven-point Likert scale (strongly agree to strongly disagree) to understand whether the respondents perceive that this digital transformation was performed at the right time from their perspective, whether they perceive that the competitors of the firm were also moving towards this type of an innovation (i.e., was it an industry trend), and whether timing had a positive influence on the outcome of this digital transformation.

Additionally, I measure the duration by asking the respondents what if any role the long duration of the digital transformation had on the program outcome. I measure their responses on a seven-point Likert scale (strongly agree to strongly disagree) to understand whether they perceive that the digital transformation program took longer than expected, whether there was fatigue at the team level and firm level with resources needed to complete the program, how long it took, and whether factors outside the control of the program, such as economic crises, firm-level crises, etc., had an adverse impact due to the long duration of the program.

Finally, I measure the dependent variable degree of success, also using a seven-point Likert scale (extremely successful to extremely unsuccessful) where the respondents were asked whether they perceive the digital transformation program to be successful or unsuccessful.

Table 3. Survey Instrument

Variable	Scale	Question
Gender (Select one)	Not applicable	Gender ○ Male ○ Female
Age (Select one)	Not applicable	Age ○ 21-30 ○ 31-40 ○ 41-50 ○ 51-60 ○ 61 and above
Relationship to the program (Select one)	Not applicable	Relationship to the program ○ User ○ Project team ○ Executive
Attributes of this innovation (7-point Likert, strongly agree to strongly disagree)	Perceived innovation attributes (Ostlund, 1974)	○ This innovation was perceived to be superior to what it superseded ○ This innovation was perceived as consistent with existing values, habits and past experiences of the potential adopter ○ This innovation was difficult to understand and use ○ This innovation was available for trial before it was broadly used ○ The results of this innovation were apparent and possible to communicate to others
Presence of opinion leaders (7-point Likert, strongly agree to strongly disagree)	Flynn's opinion leadership (Flynn et al., 1996)	○ The program had key leaders whose opinions influenced others ○ The program had key leaders who other people came to for advice ○ These key leaders were able to persuade their followers ○ The followers repeated to other people things that their key leaders told them ○ There were key leaders that influenced their followers across every major function
Diffusion approach for innovation adoption (7-point Likert, strongly agree to strongly disagree)	Rogers adoption questionnaire (Rogers, 1963; Maloney, 2010)	○ At the start of the program, the communication targeted innovators/early adopters by using terms, such as "Be one of the first, be part of the transformation, etc." ○ The program attracted the innovators/early adopters at the start of the program by triggering the feeling of "newness/scarcity" ○ After attracting the innovators/early adopters, the communication was switched to attract others by using terms, such as "Join the many, Be part of the success, etc." ○ The program was able to attract majority of the other users by showing "social proof"
Timing (7-point Likert with strongly agree to strongly disagree)	Not applicable	○ Timing of this program was right ○ Our competitors are moving towards such innovations as well ○ Timing had a positive effect on performance

Duration (7-point Likert with strongly agree to strongly disagree)	Not applicable	<ul style="list-style-type: none"> ○ This program took longer than expected ○ There was fatigue across the firm with how long the program took ○ Other factors started adversely influencing this program due to the long duration
Program outcome (7-point Likert with extremely successful to extremely unsuccessful)	Not applicable	<ul style="list-style-type: none"> ○ How would you rate the success of this program?

* Recommended sample size calculated for 95% confidence level, 5% margin of error and 50% response distribution

CHAPTER IV

FINDINGS

Study Response

Table 4 shows the study responses. All three studies achieve statistically recommended sample size for a 95% confidence interval, 5% margin of error, and a 50% response distribution. The Digital Transformation program had a 12% response rate with 425 respondents ($N = 425$); the Digital Collaboration Hub program had a 68% response rate with 150 respondents ($N = 150$); and the Integrated Business Planning program had an 88% response rate with 53 respondents ($N = 53$).

Descriptive Statistics

As shown in Table 5, in the Digital Transformation program ($N = 425$), 292 (69%) respondents were male and 135 (31%) were female. The age of the respondents was normally distributed with a majority of them between 31-60 years old; 240 (56%) of the respondents were users, 118 (28%) project team, and 67 (16%) executives. The μ value of the degree of success for this program was 3.14 and the standard deviation (SD) was 1.68. While the project sponsor and managers perceived that this digital transformation program was less successful, the survey data showed that this project was a failure.

Table 4: Study Response

Type of Study	Firm	Study & Purpose	Perceived Outcome	Duration in Years	Population Size	Recommended Sample Size*	Sample Size (N)	Response Rate
Multiple Respondent Questionnaire Survey	MNC with 21,000 employees in 30 countries	Digital Transformation Program to standardize processes	Less Successful	3.0	3,500	347	425	12%
		Digital Collaboration Hub to improve meeting effectiveness	Successful	1.0	220	141	150	68%
		Integrated Business Planning to improve demand/supply balancing	Failure	1.5	60	53	53	88%

** Recommended sample size calculated for 95% confidence level, 5% margin of error and 50% response distribution*

Table 5: Descriptive Statistics

Variable	Value	Digital Collaboration					
		Digital Transformation (N = 425)		Hub (N = 150)		Integrated Business Planning (N = 53)	
		Count	Percent	Count	Percent	Count	Percent
Gender	Male	292	69	98	65	37	70
	Female	133	31	52	35	16	30
Age	21-30	46	11	12	8	4	8
	31-40	109	25	41	27	19	36
	41-50	145	34	47	31	15	28
	51-60	105	25	41	27	14	26
	61-above	20	5	9	7	1	2
Relationship to Program	User	240	56	91	61	31	58
	Project Team	118	28	49	33	12	23
	Executive	67	16	10	6	10	19
Degree of Success	μ	3.14		2.27		3.11	
	SD	1.68		1.27		1.41	
		Failure		Success		Failure	
Distribution	Normal						

As shown in Table 5, the Digital Collaboration Hub program ($N = 150$) was 98 (65%) male and 52 (35%) female. The majority of the respondents again were between 31-60 years old; 91 (59%) of the respondents were users, 49 (33%) project team, and 10 (6%) were key users. The μ value of the degree of success for this program was 2.27, and SD was 1.27. The project sponsor and managers perceived that this digital transformation program was successful, and the survey data supported that.

The Integrated Business Planning program ($N = 53$) was 37 (70%) male and 16 (30%) female. The majority of the respondents were again between 31-60 years old; 31 (58%) of the respondents were users, 12 (23%) project team, and 10 (19%) key executives. The μ value of the degree of success for this program was 3.11, and SD was 1.41. The project sponsor and managers perceived that this digital transformation program was a failure, and the survey data supported that.

Test of Reliability

Item reliability indicates how consistently a set of instruments measures an overall response, and Cronbach's Alpha is one measure of reliability (Cronbach, 1951). For analysis of reliability, we used Cronbach's Alpha as a measure for construct reliability. As per Nunnally (1978), the nearer the value of Cronbach's alpha is to 1, the more reliable are the results. A value of Cronbach's alpha around 0.6 in general should be acceptable, and greater than 0.8 shows good reliability of questions measuring the construct that they are looking to measure (Moss et al., 1998a).

From Table 6, Cronbach's Alpha scores are above 0.6 for innovation attributes, opinion leadership, diffusion approach, timing, and duration and hence are acceptable (Moss et al., 1998a). The scores of 0.6 or above across all three studies implies that the scales have good reliability and can be used in future studies to measure these variables in the context of digital transformation.

Correlation Analysis of Variables

Table 7 includes the Pearson correlations between the variables. Since each construct was measured by multiple questions, the average score of these items was taken and this score was then used for correlation and regression analysis (Wang & Benbasat, 2007). According to Field (2005), correlation coefficients should not go beyond 0.8 to avoid multicollinearity. Since the highest

Table 6: Item Reliability

Independent Variables	Scale	No. of Items	Digital Transformation	Digital Collaboration Hub	Integrated Business Planning
			(<i>N</i> = 425)	(<i>N</i> = 150)	(<i>N</i> = 53)
			Cronbach Alpha	Cronbach Alpha	Cronbach Alpha
Innovation Attributes	Ostlund, (1974)	5	0.80	0.73	0.62
Opinion Leadership	Flynn's Opinion Leadership Scale (1996)	5	0.88	0.94	0.69
Diffusion Approach	Rogers Adoption Questionnaire (1962)	4	0.87	0.89	0.91
Timing	—	3	0.75	0.76	0.67
Duration	—	3	0.78	0.90	0.79

Table 7: Pearson Correlations of Variables

	μ	SD	1	2	3	4	5	6
Digital Transformation (N = 425)								
Innovation Attributes (1)	3.79	1.38	1.00					
Opinion Leadership (2)	3.04	1.13	0.62	1.00				
Diffusion Approach (3)	3.66	1.33	0.62	0.57	1.00			
Timing (4)	3.61	1.35	0.69	0.55	0.56	1.00		
Duration (5)	3.61	1.37	-0.31	-0.28	-0.23	-0.36	1.00	
Degree of Success (6)	3.14	1.68	0.75	0.60	0.56	0.74	-0.35	1.00
Digital Collaboration Hub (N=150)								
Innovation Attributes (1)	2.46	0.95	1.00					
Opinion Leadership (2)	3.33	1.29	0.43	1.00				
Diffusion Approach (3)	3.44	1.26	0.54	0.70	1.00			
Timing (4)	2.67	1.08	0.59	0.43	0.55	1.00		
Duration (5)	4.25	1.35	-0.19	-0.03	-0.08	-0.04	1.00	
Degree of Success (6)	2.27	1.27	0.58	0.31	0.46	0.52	-0.20	1.00
Integrated Business Planning (N = 53)								
Innovation Attributes (1)	3.12	0.98	1.00					
Opinion Leadership (2)	2.75	1.00	0.55	1.00				
Diffusion Approach (3)	3.46	1.35	0.52	0.60	1.00			
Timing (4)	3.39	1.28	0.66	0.54	0.57	1.00		
Duration (5)	2.56	1.15	-0.20	-0.05	-0.18	-0.26	1.00	
Degree of Success (6)	3.11	1.41	0.54	0.58	0.48	0.67	-0.29	1.00

correlation coefficient is 0.75 between innovation attributes and degree of success, which is still less than 0.8, there is no multicollinearity problem in our research.

For innovation attributes, in Study 1 ($N = 425$), the μ was 3.79 and SD was 1.38. However, in Study 2 ($N = 150$), the μ was 2.46 and SD was 0.95. Similarly, in Study 3 ($N = 53$), the μ was 3.12 and SD was 0.98. What we can conclude from these is that in Study 1 and Study 3, respondents on average somewhat agreed or neither agreed/disagreed that these digital transformations attributes: a) were relatively advantageous over the previous option, b) were compatible with the users' habits, c) were simple to use, d) benefits were observable, and e) were available on trial. However, in Study 2 the respondents on average agreed to all.

For the opinion leadership, in Study 1, the μ was 3.04 and SD was 1.13. However, in Study 2, the μ was 3.33 and SD was 1.29. Similarly, in Study 3, the μ was 2.75 and SD was 1.00. What we can conclude from these is that in Study 1 and Study 3 where opinion leaders were utilized, the respondents on average agreed or somewhat agreed that the program had opinion leaders who influenced their followers. Study 2 did not use the opinion leaders but used the Hypodermic Needle model of direct communication (Rogers, 1962). Hence the respondents *somewhat agreed* that the program had opinion leaders that influenced their followers.

For diffusion approach, in Study 1, the μ was 3.66 and SD was 1.33. However, in Study 2, the μ was 3.44 and SD was 1.26. Similarly, in Study 3, the μ was 3.46 and SD was 1.35. What we can conclude from these is that the respondents somewhat agreed or neither agreed or disagreed that the diffusion approach of innovation adoption was used where innovators and early adopters (first 16%) were initially attracted to the program by stimulating a sense of scarcity and the early majority and late majority (next 68% of users) were attracted to the program by demonstrating social proof.

For innovation timing, in Study 1, the μ was 3.61 and SD was 1.35. However, in Study 2, the μ was 2.67 and SD was 1.08. Similarly, in Study 3, the μ was 3.39 and SD was 1.28. We can conclude from these that the respondents somewhat agreed or neither agreed or disagreed that the digital

transformation was implemented at the right time and other firms in the industry were also pursuing similar digital transformations.

For duration, in Study 1, the μ was 3.61 and SD was 1.37. We can conclude from this that the respondents on average somewhat agreed that the duration of this digital transformation was too long and other factors outside the control of the program started impact it. However, in Study 2, the μ was 4.25 and SD was 1.35. Thus on average the respondents somewhat disagreed that the duration of the digital transformation was too long. This is understandable since this program was about one year. Similarly, in Study 3, the μ was 2.56 and SD was 1.15. Thus the respondents agreed that the duration of the digital transformation was too long. This program was originally intended to take one year but it went longer than expected.

For the outcome variable degree of success, the μ in Study 1, was 3.41 and SD was 1.68. The respondents on average felt that the program was slightly successful. However, in Study 2, the μ was 2.27 and SD was 1.275. On average the respondents felt that the program was moderately successful. In Study 3, the μ was 3.11 and SD was 1.41. What we can conclude from that is on average the respondents felt that the program was slightly successful.

Regression Modeling

Because Multiple Regression (MR) can be used to analyze the relationship between a single dependent variable and several independent variables (Hair, Anderson, Tatham, & Black, 1998), I use MR analysis to measure the effects of innovation attributes, opinion leadership, diffusion approach, timing, and duration on the outcome, degree of success of a digital transformation,. A MR model is also considered to be valid when the following assumptions are fulfilled: 1) linearity of the relationship between dependent and independent variables; 2) constant variance of the error term, i.e., homoscedasticity; 3) independence of the error terms; 4) normality of the error term distribution and individual variables; and 5) the predictor variables are not correlated among themselves, i.e., multicollinearity (Churchill, 1995).

Table 8: Multiple Regression Summaries

	Digital Transformation (N = 425)					Digital Collaboration Hub (N = 150)					Integrated Business Planning (N = 53)				
	Est.	Std. β	t Ratio	Sig. (p)	VIF	Est.	Std. β	t Ratio	Sig. (p)	VIF	Est.	Std. β	t Ratio	Sig. (p)	VIF
Innovation Attributes (H ₁)	0.46	0.38	8.60	<.0001	2.49	0.47	0.35	4.13	<.0001	1.77	0.10	0.07	0.52	0.607	1.98
Opinion Leadership (H ₂)	0.18	0.12	3.13	0.0019	1.84	-0.06	-0.06	-0.70	0.4854	1.96	0.43	0.31	2.31	0.025	1.86
Diffusion Approach (H ₃)	0.06	0.05	1.21	0.2265	1.83	0.17	0.17	1.68	0.09	2.40	-0.03	-0.03	-0.20	0.845	1.86
Timing (H ₄)	0.44	0.36	8.64	<.0001	2.16	0.28	0.24	2.87	0.0048	1.75	0.47	0.43	3.03	0.004	2.13
Duration (H ₅)	-0.07	-0.06	-1.92	0.0557	1.16	-0.10	-0.11	-1.69	0.09	1.05	-0.19	-0.15	-1.49	0.143	1.09
R ²											0.5437				
Adjusted R ²											0.4951				
Sig F											<.0001				
RMSE											1.0015				

p-value is significant at the 0.05 level for items that are bolded

Overall Model Fit

A well-fitting regression model results in predicted values close to the observed data values. To evaluate model fit, I use three statistics that are used in Ordinary Least Squares (OLS) regression: R^2 (or Adjusted R^2), Overall F -test, and Root Mean Square Error (RMSE) (Hair et al., 2010, p. 186).

R^2 is a statistical measure of how close the data are to the fitted regression line. Adjusted R^2 is a modified version of R^2 that has been adjusted for the number of predictors in the model. The adjusted R^2 increases only if the new term improves the model more than what would be expected by chance and decreases if the new term does not improve the model more than what would be expected by chance.

The F -test for overall significance indicates whether the linear regression model provides a better fit to the data than a model that contains no independent variables. The F -test for overall significance has the following two hypotheses: 1) the null hypothesis states that the model with no independent variables fits the data as well as the current model, and 2) the alternative hypothesis states that the current model fits the data better than the intercept-only model.

RMSE is the square root of the variance of the residuals and indicates how close the observed data points are to the model's predicted values. RMSE is the most important criterion for fit if the main purpose of the model is prediction. The parameter estimates report summarizes the effect of each predictor and provides five important items: 1) estimate, 2) standardized β , 3) t -ratio, 4) significance (p -value), and 5) variance inflation factor (VIF). Estimate gives the parameter estimates for each item and estimates the model coefficients. Standardized β shows parameter estimates for a regression model where all of the terms have been standardized to a mean of 0 and variance of 1. t -ratio tests whether the true value of the parameter is zero. The t -ratio is the ratio of the estimate to its standard error. p -value indicates the significance for the test that the true parameter value is zero, against the two-sided alternative that it is not. VIF shows the variance inflation factor for each item in the model. High VIFs indicate a collinearity issue among the terms in the model (Multicollinearity, 2018).

Digital Transformation Program (N = 425). The overall model is significant at the 5% level with a Sig F of <0.0001. Such a small *p*-value is considered evidence that there is at least one significant effect in the model. The R² value of 66.81% (and Adjusted R² of 66.41%) indicates that the model explains a large amount of the variance. The RMSE of 0.9 indicates a good fit.

Digital Collaboration Hub Program (N = 150). The overall model is significant at the 5% level with a Sig F of <0.0001. Such a small *p*-value is considered evidence that there is at least one significant effect in the model. The R² value of 40.86% (and Adjusted R² of 38.81%) indicates that the model explains a large amount of the variance. The difference between the R² and Adjusted R² is 2.05% in this study (*N* = 150) in comparison to Study 1 (*N* = 425) where the difference is 0.40%. This difference is because of the smaller sample size (*N*). In general, as sample size increases, the difference between R² and Adjusted R² approaches zero because R² becomes less biased and the standard error of Adjusted R² gets smaller approaching zero in the limit. The RMSE of 0.9 indicates a good fit.

Integrated Business Planning Program (N = 53). The overall model is significant at the 5% level with a Sig F of <0.0001. Such a small *p*-value is considered evidence that there is at least one significant effect in the model. The R² value of 54.37% (and Adjusted R² of 49.51%) indicates that the model explains a large amount of the variance. The difference between R² and Adjusted R² in this model is 4.86% in this study (*N* = 53) in comparison to Study 1 (*N* = 425) where the difference is 0.40% and Study 2 (*N* = 150) where the difference is 2.05%. The RMSE of 1.0 indicates a good fit.

Hypotheses Testing

H₁: Perceived innovation attributes have a positive effect on the degree of success of a digital transformation program.

Digital Transformation Program (N = 425). I reject the null hypothesis because innovation attributes had a significant positive effect on the degree of success in this dataset. For a unit increase in innovation attributes, the degree of success increased by 46%. The VIF of 2.49 is less than 4.0, hence there is no problems of multicollinearity (Harris, Fotheringham, & Juggins, 2010).

Digital Collaboration Hub Program (N = 150). I reject the null hypothesis because innovation attributes had a significant positive effect on the degree of success in this dataset. For a unit increase in innovation attributes, the degree of success increased by 47%. The variance inflation factor (VIF) of 1.77 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Integrated Business Planning Program (N = 53). I fail to reject the null hypothesis. Innovation attributes did not have a significant positive effect on the degree of success in this dataset. In this study, several of the respondents mentioned that the key technology used in this program was not significantly better than the option that was currently available to them, and hence they did not feel that the innovation attributes significantly influenced the outcome.

Our findings are supported in prior research papers of innovation adoptions where innovation attributes were the strongest predictors of success (Tornatzky & Klein, 1982; Al-Gahtani, 2003; Arts et al., 2011; Min et al., 2018). In both studies where innovation attributes were significant, they were one of the strongest predictors of degree of success.

H₂: The degree to which opinion leaders within the firm are involved in the digital transformation is positively associated with the success of the digital transformation.

Digital Transformation Program (N = 425). I reject the null hypothesis. Opinion leadership had a significant positive effect on the degree of success in this dataset. For a unit increase in opinion leadership, the degree of success increased by 18%. The standardized β value of 0.12 shows that the effect is not as strong as 0.38 for innovation attributes or 0.36 for timing. While opinion leaders' positive effects on degree of success was significant, it was still about one-third less strong than innovation attributes or timing. The VIF of 1.84 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Digital Collaboration Hub Program (N = 150). I fail to reject the null hypothesis. Opinion leadership did not have a significant positive influence on the degree of success in this dataset because this program did not utilize opinion leaders to diffuse innovation but rather used the

Hypodermic Needle Model of communication where mass communication about the innovation is sent directly to users (Rogers, 1963).

Integrated Business Planning Program (N = 53). I reject the null hypothesis. Opinion leadership had a significant positive effect on the degree of success in this dataset. For a unit increase in opinion leadership, the degree of success increased by 43%. The standardized β value of 0.31 shows that the effect is not as strong as 0.43 for timing, but it is still significant. The VIF of 1.86 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

These findings are consistent with prior studies of innovation diffusion where opinion leaders, if utilized, had a significant influence on innovation adoption influencing their followers to adopt the innovation (Cho et al., 2012; Seebauer, 2015; Turnbull & Meenaghan, 1980; Valente & Davis, 1999; Liu et al., 2017; Granovetter, 1983; Brown et al., 2017). In the Digital Transformation program ($N = 425$) and Integrated Business Planning ($N = 53$), where the opinion leaders were identified, these opinion leaders seemed to have a significant influence on degree of success. While the effects were still not as strong as innovation attributes or timing, it was nevertheless significant, which supports our hypothesis that when opinion leaders are utilized in digital transformation programs, they have a significant positive effect on the degree of success.

However, in the Digital Collaboration Hub ($N = 150$,) program respondents were not familiar with opinion leaders or the role they played in diffusing this innovation since they directly received mass media and direct communications about the benefits of using the Surface Hub technology to improve meeting effectiveness and collaboration and to avoid travel costs to attend meetings in person. This type of communication is also called the Hypodermic Needle Model (Rogers, 1963). My findings are supported in other studies similar to the Digital Collaboration Hub, where simple innovations that are easy to observe and try outs are adopted through direct communication with the user (Risselada, 2014; O’Cass & Fenech, 2003; Mattila, Karjaluoto, & Pento, 2003; Lu, Yu, Liu, & Yao, 2003).

H₃: Digital transformations that rely on a diffusion approach are more successful than those that rely on change management alone.

Digital Transformation Program (N = 425). I fail to reject the null hypothesis. The diffusion approach did not have a significant positive influence on the degree of success of a digital transformation program in this data sample. The *p*-value was greater than 5% ($p = 22.65\%$) and was not significant.

Digital Collaboration Hub Program (N = 150). I fail to reject the null hypothesis. The diffusion approach did not have a significant positive influence on the degree of success of a digital transformation program in this data sample. The *p*-value was greater than 5% ($p = 9\%$) and was not significant.

Integrated Business Planning Program (N = 53). I fail to reject the null hypothesis. The diffusion approach did not have a significant positive influence on the degree of success of a digital transformation program in this data sample. The *p*-value was greater than 5% ($p = 8.45\%$) and was not significant.

These findings are supported in the MacVaugh & Schiavone (2010) literature review and historical case analysis of diffusion of innovation papers to show the limitations with the diffusion approach of innovation adoption. The authors recommended that “conditions” and “domain” play a more important role in innovation adoption than the diffusion approach. If the switching costs are high (“conditions”) and the individual, community, or market/industry (“domain”) allows avoiding the innovation, the diffusion approach to innovation adoption is not effective. An example of this was noticed in the Digital Transformation Program ($N = 425$) where certain users were provided an exception to continue using the old user interface (UI) as they perceived that using the new UI would slow them down since they were not still experts at using it. This was in spite of the knowledge that the old UI would not exist after some time and they would eventually have to switch to the new UI. Since these functions already had severe throughput challenges (“conditions”) and could potentially cause firm-level disruption (“domain”), the firm leadership had to make an exception as they were

fearful of the impact on operations (“conditions”). This highlights how the conditions and domain can be limiting factors for the diffusion approach to be successful.

Similarly, the Lyytinen & Damsgaard (2001) study on Electronic Data Interchange (EDI) adoption by firms also supports our finding that a diffusion approach may not be effective in adoption of all complex and networked IT solutions since some innovations are “learning intensive” and are dependent on the “network.” This was clear in the Digital Collaboration Hub ($N = 150$) where a large group of users avoided training programs to familiarize themselves with the Surface Hub technology, saying that they were busy and short of time already or felt overwhelmed that they had to now learn another new technology (“learning intensive”). Since this innovation was optional and not mandatory for use as part of their jobs (“network”), the firm did not enforce a strict policy that all users had to attend training. The users could still do their jobs without using this innovation. Hence the diffusion approach in this case did not succeed as the “learning intensiveness” and “network” factors limited the diffusion approach from being successful.

H₄: Innovation timing is positively associated with the success of a digital transformation program.

Digital Transformation Program ($N = 425$). I reject the null hypothesis. Innovation timing had a significant positive influence on the degree of success of the digital transformation program in this dataset. For a unit increase in innovation timing, the degree of success of digital transformation went up by 44%. The VIF of 2.16 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Digital Collaboration Hub Program ($N = 150$). I reject the null hypothesis. Innovation timing had a significant positive influence on the degree of success of the digital transformation program in this data sample. For a unit increase in innovation timing, the degree of success of digital transformation went up by 28%. The VIF of 1.75 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Integrated Business Planning Program (N = 53). I reject the null hypothesis. Innovation timing had a significant positive influence on the degree of success of the digital transformation program in this data sample. For a unit increase in innovation timing, the degree of success of digital transformation went up by 47%. The VIF of 2.13 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010). The standardized β of 0.43 is stronger than opinion leader 0.31, showing that timing was the strongest predictor of outcome.

These findings are consistent with prior studies of innovation adoption where the optimal timing to introduce an innovation was very important for its successful adoption (Gilbert & Birnbaum-More, 1996; Mann, 2005; Kuckertz & Wagner, 2010; Kim, 2011; Low et al., 2011; Mezghani, 2014; Hossain, 2001; Premkumar et al., 1997; Crum et al., 1996; Patterson et al., 2003). In both studies, the digital transformation program ($N = 425$) and the digital collaboration hub program ($N = 150$), respondents felt that the timing of this program was right, competitors of the firm were also moving towards this type of innovation, and the timing of this innovation had a positive effect on the degree of success.

H₅: Duration has a negative effect on digital transformation success with longer programs being less successful.

Digital Transformation Program (N = 425). I fail to reject the null hypothesis. Duration did not have a significant negative influence on the degree of success in this dataset at the 5% level; but at the 10% level (or 90% confidence interval), it was significant and, as hypothesized, had a negative effect on degree of success. For a unit increase in duration, the degree of success decreased by 7%. The VIF of 1.16 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Digital Collaboration Hub Program (N = 150). I fail to reject the null hypothesis. Duration did not have a significant negative influence on the degree of success in this dataset because this program was about one year in comparison to the digital transformation program ($N = 425$) that was three years. Duration did not have a significant negative influence on the degree of success in this dataset at the 5% level; but at the 10% level (or 90% confidence interval), it was significant and, as

hypothesized, had a negative effect on degree of success. For a unit increase in duration, the degree of success decreased by 10%. The VIF of 1.05 is less than 4.0, hence there is no problems of multicollinearity (Harris et al., 2010).

Integrated Business Planning Program (N = 53. I fail to reject the null hypothesis. Duration did not have a significant negative influence on the degree of success in this dataset because this program was about a year and one-half in comparison to the digital transformation program ($N = 425$) that was three years.

These findings are consistent with prior studies where innovations with longer durations were adversely impacted by factors that were outside the control of the program, such as economy and firm-level factors (Archibugi et al., 2013b; Filippetti & Archibugi, 2011; Kuznetsov & Simachev, 2010; Paunov, 2012) and fatigue at the team-level resulting in burnout and turnover (Fry & Cohen, 2009; Ng & Feldman, 2008; Lamberg, 2004; Worrall & Cooper, 1999; Feddock et al., 2007; Estryn-Béhar et al., 2007; Gilbert-Ouimet et al., 2018; Kuroda & Yamamoto, 2016; Lo et al., 2016).

CHAPTER V

MACHINE LEARNING

Introduction to Machine Learning

Machine learning (ML) is a part of artificial intelligence that uses statistical theories to build mathematical models to enable accurate predictions or inferences from a dataset. ML is also often referred to as “statistical learning,” “computational learning,” and “pattern recognition” (Alexander, 2013). Application of ML methods to large databases is called “data mining.” The aim of data mining can be prediction of future events, knowledge discovery of patterns, and trends and outlier detection for fraud and churning (Alpaydin, 2009).

There are primarily three major ML types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is when a model is trained on an existing dataset (often referred to as a training dataset) to learn how independent variables influence a certain outcome (dependent variable). Once the model is trained, it can use these learnings to predict outcomes in future datasets. Applications of supervised learning methods are in predicting customer churn, sentiment analysis, etc. Commonly used supervised learning techniques are Regression (linear or polynomial), Decision Tree, Random Forest, and Classification methods (KNN, Trees, Logistic Regression, Naïve Bayes, and Support Vector Machines).

Unsupervised learning is when a model is provided a dataset and it finds patterns and relationships to create clusters and associations. Commonly used unsupervised learning methods for clustering are SVD, PCA and K-means and for association are Apriori and FP-Growth.

Common applications of the unsupervised ML method are in shopping basket recommendations (customer who bought X also bought Y and Z in e-commerce transactions). Reinforcement learning is when a person actively interacts with the model and the model learns from these interactions and predicts future decisions. A common application of this method is in Netflix movie recommendations and social media feeds sent to users based on prior clicks, online activity, and user likes.

Complementary Role of Machine Learning

ML techniques can be used to complement theoretical, explanatory research studies by developing new statistical procedures that provide improved performance measures or hypothesis testing with lower type-1 error (rejection of a true null hypothesis) and higher power and resampling procedures that lead to better estimations (Alpaydin, 2011). Also, under conditions of moderate nonlinearity, regression has shown sub-par performance, whereas Decision Tree-type ML techniques provide substantially better bias reduction and more consistent 95% confidence interval coverage (Lee, Lessler, & Stuart, 2010).

Feature Importance

Feature (variable) importance is a post-prediction model development effort where we build a prediction model for one or more of the model types; and, using the prediction model and “leave-one-out” method, we assess the relative contributions of the independent variables. The main purpose of performing “feature importance” is to measure a variable’s importance by calculating the increase of the model’s prediction error after permuting the variable. A variable is important if permuting its values increases the model error, because the model relied on the variable for its prediction. A variable is “unimportant” if permuting its value does not result in a change of model error because the model ignored the variable during prediction (Breiman, 2001; Fisher, Rudin, & Dominici, 2018).

Leave-one-out is a cross-validation technique. Cross-validation is a technique used to protect against overfitting in a predictive model when datasets are small. In cross-validation, the data is partitioned into a fixed number of folds (K), the analysis is run on each fold, and then the average overall error is estimated. Leave-one-out cross-validation (LOOCV) is a K-fold cross-validation

where $K = N$ (the number of data points in the set). The function approximator in this case is trained on all the data N separate times except for one point and a prediction is made for that point. The primary purpose of cross-validation is to check how well a model generalizes to new data. The LOOCV estimates are obtained by averaging the N scores obtained for the different repetitions.

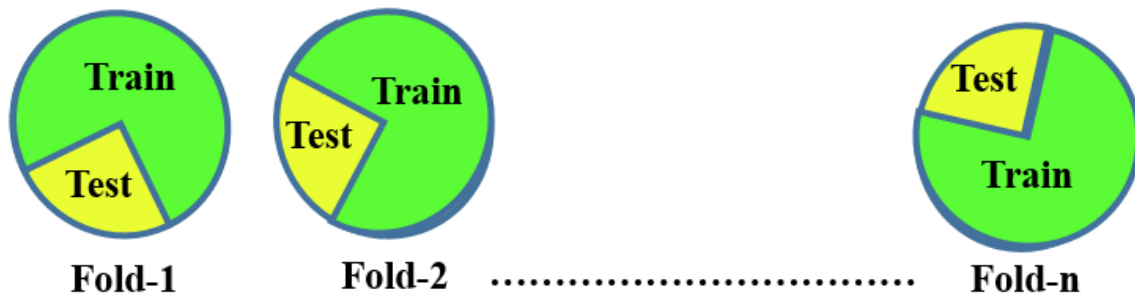


Figure 4: Leave-One-Out Cross-Validation (LOOCV)

LOOCV Decision Tree Technique

In this section, I use a LOOCV approach in combination with Decision Tree to measure feature importance and check how well my model generalizes to new data. A Decision Tree algorithm is a ML technique where a top-down tree is built starting with a root node and partitioning data into subsets that contain nodes with similar values. There are three major reasons why I selected a Decision Tree algorithm over others. 1) Decision Trees implicitly perform variable screening and feature selection. As I input the data into the Decision Tree, the top few nodes on which the tree is split are essentially the most important variables, and this feature selection is done automatically (Sugumaran, Muralidharan, & Ramachandran, 2007). 2) Other ML methods such as Naïve Bayes, Maximum Entropy Classification, and Support Vector Machines have shown to perform poorly on sentiment classification (Pang, Lee, & Vaithyanathan, 2002). 3) Decision Trees are not black box algorithms like Support Vector Machines, Neural Networks, etc. and are easy to visualize and explain.

I used the KNIME 3.5.3 Advanced Analytics platform to perform ML. I coded my outcome variable as S (success) when Likert value was 1 (extremely successful), 2 (moderately successful),

and 3 (slightly successful). I coded it as F (failure) when Likert values were 4 (neither successful nor unsuccessful), 5 (slightly unsuccessful), 6 (moderately unsuccessful) and 7 (extremely unsuccessful).

Digital Transformation Program (N = 425). As shown in Figure 5, I perform cross-validation iterations. Partitions were then sampled randomly from the input table. The Training data had 383 records, and Testing data had 42 records. I then passed the Training data into a Decision Tree Learner where I used the Gini index, which is a binary decision tree with each node having only two children. As shown in Figure 6, the Decision Tree ML model proposed that *timing* was the most important variable, followed by *innovation attributes* and *opinion leadership*. Table 9 compares the outputs from the MR and ML models. While the standardized β values of innovation attributes (0.38) and timing (0.36) are fairly close and the p -value is $<.0001$, ML identified *timing* as the most important variable in this dataset, showing the superior accuracy of ML over MR in identifying variable importance.

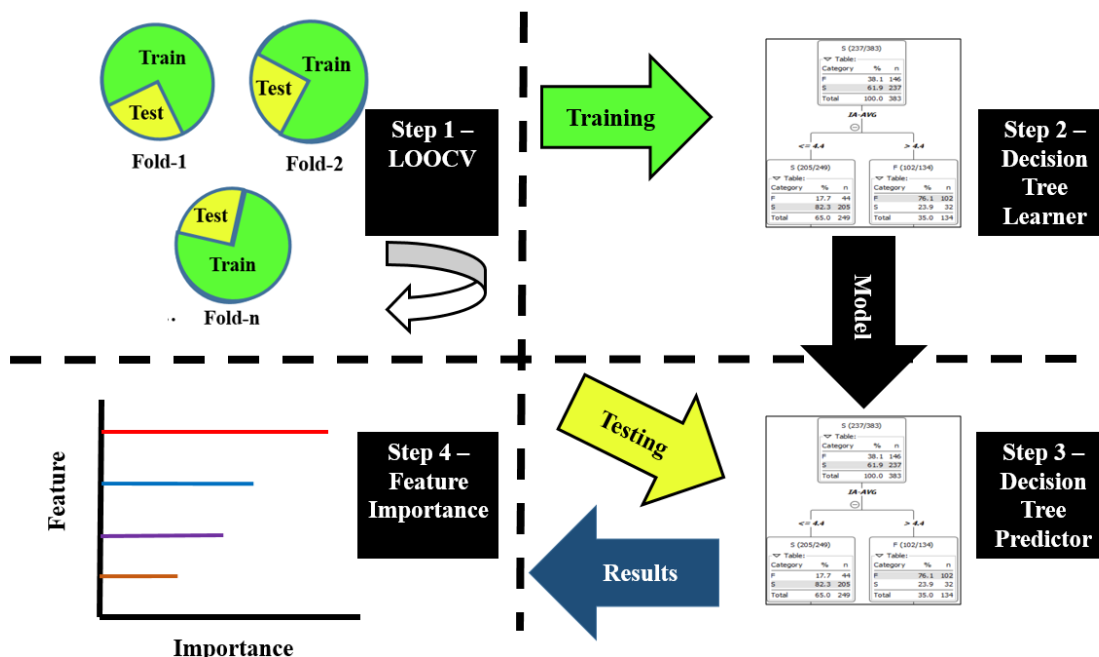


Figure 5: LOOCV Process for Feature Importance

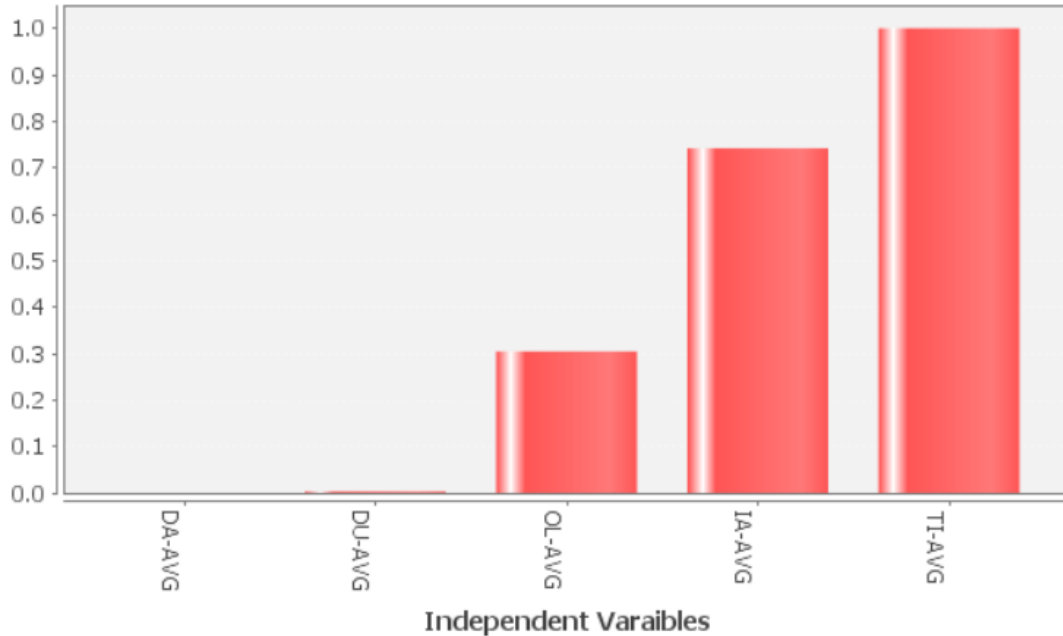


Figure 6: Importance of Variables in Digital Transformation Program

Table 9: MR Versus ML for Variable Importance in Digital Transformation Program

Digital Transformation Program ($N = 425$)	Multiple Regression (MR)		Machine Learning (ML)	
	p -value	Std. β	Variable Importance	Variable Importance
Innovation Attributes	<.0001	0.38	1	2
Timing	<.0001	0.36	2	1
Opinion Leadership	0.0019	0.12	3	3
Duration	0.0557	-0.06	4	4
Diffusion Approach	0.2265	0.05	5	5

Digital Collaboration Hub ($N = 150$). As shown in Figure 5, I perform cross-validation iterations. Partitions were then sampled randomly from the input table. The Training data had 135 records and Testing data had 15 records. I then passed the Training data into a Decision Tree Learner where I used the Gini index, which is a binary Decision Tree with each node having only two children. As shown in Figure 7, the Decision Tree ML model proposed that *innovation attribute* was the most important variable, followed by *timing* and *diffusion approach*. Table 10 compares the outputs from MR and ML models. Both models had similar results for variable importance in this dataset.

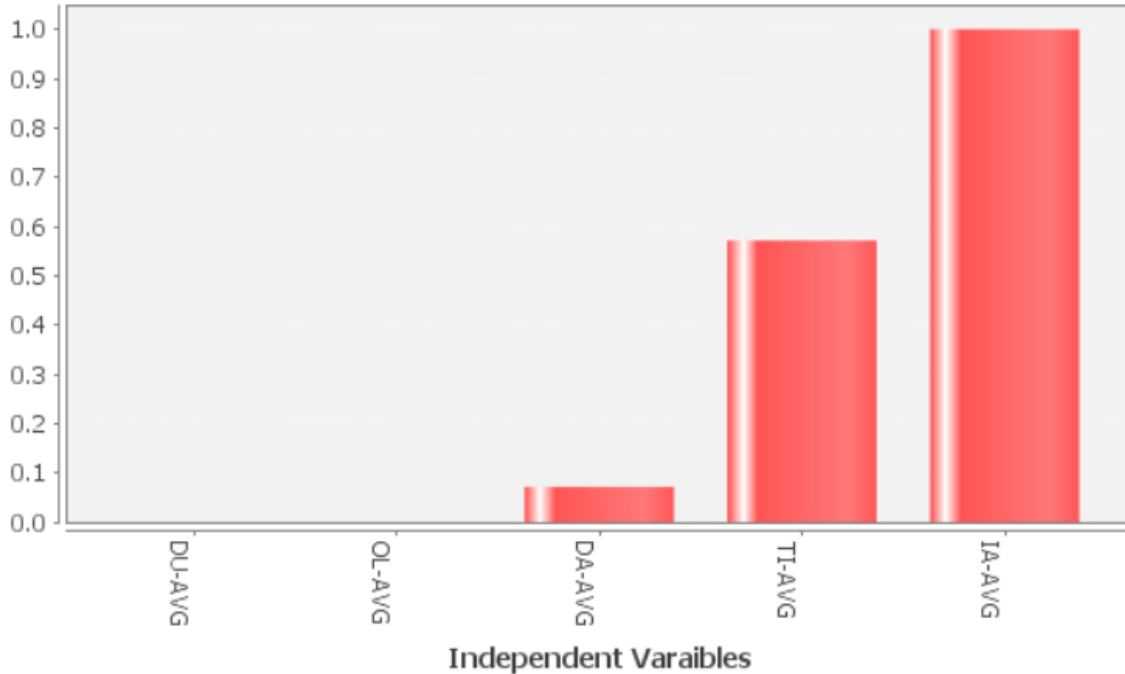


Figure 7: Importance of Variables in Digital Collaboration Hub

Table 10: MR Versus ML for Variable Importance in Digital Collaboration Hub

Digital Collaboration Hub (N = 150)	Multiple Regression (MR)		Machine Learning (ML)	
	p-value	Std. β	Variable Importance	Variable Importance
Innovation attributes	<.0001	0.35	1	1
Timing	<.0048	0.24	2	2
Diffusion approach	0.0900	0.17	3	3
Opinion leadership	0.4854	-0.06	4	4
Duration	0.0900	-0.10	5	5

Integrated Business Planning (N = 53). As shown in Figure 8, I perform cross-validation iterations. Partitions were then sampled randomly from the input table. The Training data had 48 records and Testing data had 5 records. I then passed the Training data into a Decision Tree Learner where I used the Gini index, which is a binary decision tree with each node having only two children. As shown in Figure 8, the Decision Tree ML model proposed that *opinion leadership* was the most important variable, followed by *timing* and *innovation attributes* in this dataset. Table 11 compares

the outputs from MR and ML models. ML again was more precise in identifying the most important variable in comparison to the MR model.

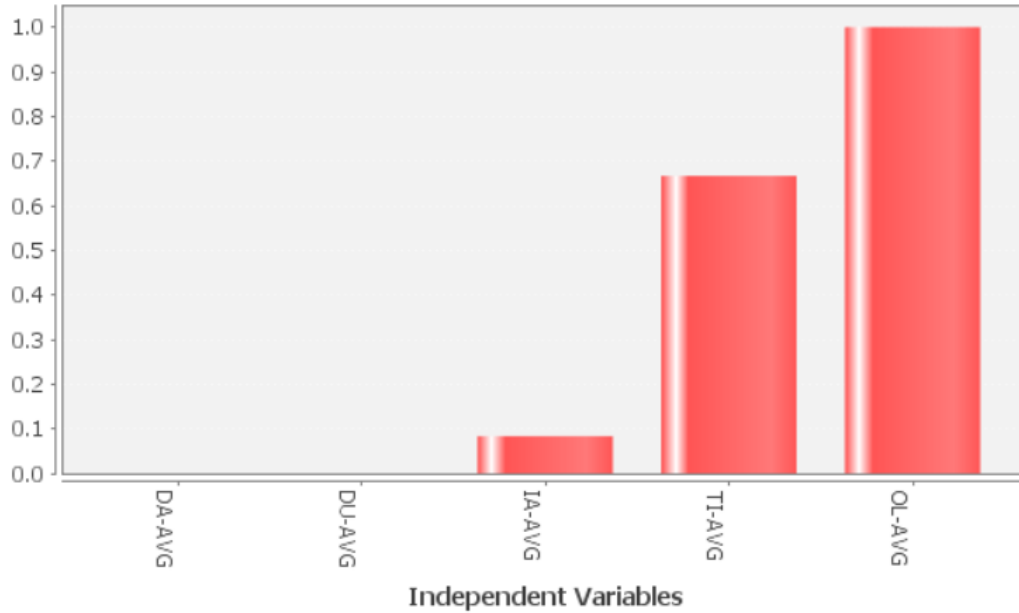


Figure 8: Importance of Variables in Integrated Business Planning

Table 11: MR Versus ML for Variable Importance in Integrated Business Planning

Integrated Business Planning (<i>N</i> = 53)	Multiple Regression (MR)		Machine Learning (ML)	
	<i>p</i> -value	Std. β	Variable Importance	Variable Importance
Timing	0.004	0.43	1	2
Opinion leadership	0.025	0.31	2	1
Innovation attributes	0.607	0.07	3	3
Duration	0.143	-0.15	4	4
Diffusion approach	0.845	-0.03	5	5

Summary

In summary, ML techniques such as Decision Tree fared better than classical MR techniques to identify variable importance in the three studies that I performed. This is consistent with the Tso & Yau (2007) study where the authors compared regression analysis and Decision Tree and concluded that the Decision Tree ML technique was superior to regression in identifying variable importance.

Other studies have also employed the Decision Tree ML technique for measuring variable importance, thereby supporting my approach and findings (de Oña, de Oña, & Calvo, 2012; Yu, Haghghat, Fung, & Yoshino, 2010; D'Heygere, Goethals, & De Pauw, 2003).

CHAPTER VI

CONCLUSION

Research Summary

Digital transformation is one of today's keys to firm success. Digital leaders embracing the potential of cutting edge technologies such as automation, artificial intelligence, big data, etc. to increase efficiency, reduce risk, and improve customer experience will outperform their peers in every industry (Bock et al., 2017; Westerman et al., 2012). To become digital leaders, firms will have to successfully execute the integration of digital and physical components and transform their business models (Berman, 2012).

However, 84% of companies fail at digital transformation with significant disruption to their business operations and unwillingness to innovate in the future (Rogers, 2016). This year alone, firms are expected to invest \$1.3 trillion in some form of digital transformations. But more than 70% of them will not meet their objectives, resulting in \$900 billion of scarce resources being squandered away at a shocking scale (Zobell, 2018).

Based on the Engaged Scholarship approach (Van de Ven, 2007) and the Diffusion of Innovation Theory (Rogers, 1963), I investigated the impact of the study variables in three separate digital transformation programs for a multinational firm to find out whether my findings are reliable across multiple programs and whether the results are generalizable. The overall model in all three studies were significant at the 5% level ($p < 0.0001$), and the model fit statistics

were good, showing that the model fit the data well and there were at least one or more variables that significantly influenced the digital transformation outcome.

Research Contributions

While current research has been focused on firm culture, management, and vision, it has not provided actionable intelligence to practitioners in the field performing digital transformation on how to improve success in their programs. This has resulted in a high failure rate and disruption of firm performance. This research fills that gap in knowledge by investigating new variables on the outcome of a digital transformation: a) innovation attributes, b) opinion leadership, c) diffusion approach, d) timing, and e) duration.

- *Research Contribution# 1:* In all three studies, *timing* of the digital transformation was one of the strongest predictors of digital transformation success, irrespective of the size of the program. The key research contribution here is that firms embarking on a digital transformation should pick “optimal timing” when they should pursue a certain digital capability by looking closely to what competitors are doing and the relevance to the industry. Innovation timing decision is most likely the strongest predictor of the success of a digital transformation program.
- *Research Contribution# 2:* Attributes of the key technology used in the digital transformation was the next strongest influencer of digital transformation outcome. The key research contribution here is that for a digital transformation to be successfully adopted, it is important that the key technology: a) has relative advantage over its predecessor, b) is simple to use and does not require intensive learning, c) is compatible with the users’ current habits, d) the benefits of using it are easily observable to adopters, and e) it can be used on a trial basis before committing to it permanently. It is important that the managers who are responsible for selection of the key technology keep these specific factors in mind as they review the various technology options in front of them and select a key technology to be used for the digital transformation.

- *Research Contribution# 3:* Opinion leaders had a significant positive effect on digital transformation outcomes where they were utilized. The key research contribution here is that as firms launch their digital transformation programs, it is very important to identify key opinion leaders across various functions within the firm; invest in the training and development of these opinion leaders; and provide them the necessary resources, forums, and opportunities to influence their followers.
- *Research Contribution# 4:* Surprisingly, diffusion approach did not significantly influence digital transformation program outcomes in all the three studies. The key research contribution here is that a diffusion approach of attracting innovators and early adopters (the first 16%) by stimulating “scarcity” in communications and later switching communication style to “social proof” to attract the early majority and late majority (next 68%) may have worked in the context of other innovation adoptions but has little to no significant influence in the context of digital transformations. Managers responsible for digital transformation should continue with existing change management best practices.
- *Research Contribution# 5:* Interestingly, duration did not significantly influence digital transformation outcome in all three studies at the 5% level; but at the 10% level, it had a negative effect on the outcome of the digital transformation as hypothesized. The key research contribution here is that as firms launch the program, they should keep in mind that they should not to make these programs so long that other factors outside the control of the program (e.g., economic, firm-level, etc.) start to adversely impact the outcome. Longer programs also adversely impact the team member fatigue and result in burnout and turnover.
- *Research Contribution# 6:* While regression techniques avoid overfitting the data, they perform poorly in capturing complex patterns or moderately nonlinear relationships. This can be overcome by a LOOCV type of ML technique that can learn complex patterns and is fairly robust to outliers. In the context of identifying feature importance, it is clear that LOOCV ML

techniques fared better than regression techniques and hence is valuable in accurately identifying feature importance.

To summarize, to the best of my knowledge this is the first time that innovation attributes, opinion leaders, diffusion approach, timing, and duration have been studied in the context of improving success in digital transformations intended to improve efficiency. Prior studies have not empirically tested these variables in multiple studies holding firm-level factors, such as culture, management and vision, constant and showing reliability and validity of the results across multiple digital transformation programs of different sizes.

In addition to contributing to the Diffusion of Innovation theory by applying it in the context of digital transformations, this research has also developed validated scales for innovation attributes, opinion leaders, diffusion approach, timing, and duration in the context of digital transformations with good item reliability (Cronbach's $\alpha > 0.6$) across multiple studies. Future researchers can use these scales for their research in digital transformations. In addition to contributing to theory, this research also provides practitioners with actionable intelligence that they can apply in their current digital transformations to reduce the high failure rate.

Research Limitations

As with any empirical study, this research has certain limitations. The scales used to measure the variables were in the context of innovation adoption and had to be customized for digital transformations. While we achieved recommended sample size required for making statistical inferences, we were limited in one of our studies ($N = 425$) with a low response rate of 12%. While they achieved the recommended sample size, Two of our studies ($N = 150$ and $N = 53$) had relatively smaller total numbers of participants. Survey research by design has some common method bias, and this research is no different.

Future Directions

This research of factors influencing digital transformation success was based on the Diffusion of Innovation theory (Rogers, 1963) and focused on how innovations are adopted by users. Future

research can explore other theories that are specific to adoption of information systems (IS) such as Technology Acceptance Model (TAM), which is an IS theory that models how users come to accept and use technology (Davis, 1989). It would be interesting to conduct this research in another firm to see whether the results can be replicated and also in studies with larger sample sizes.

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APPENDICES



Oklahoma State University Institutional Review Board

Date: 10/09/2018
Application Number: BU-18-51
Proposal Title: Digital Transformation: How to Beat the High Failure Rate?

Principal Investigator: NAGESH RAMESH
Co-Investigator(s):
Faculty Adviser: DURSUN DELEN
Project Coordinator:
Research Assistant(s):

Processed as: Exempt

Status Recommended by Reviewer(s): Approved

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

The final versions of any recruitment, consent and assent documents bearing the IRB approval stamp are available for download from IRBManager. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be approved by the IRB. Protocol modifications requiring approval may include changes to the title, PI, adviser, other research personnel, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms.
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any unanticipated and/or adverse events to the IRB Office promptly.
4. Notify the IRB office when your research project is complete or when you are no longer affiliated with Oklahoma State University.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact the IRB Office at 223 Scott Hall (phone: 405-744-3377, irb@okstate.edu).

Sincerely,

A handwritten signature in black ink, appearing to read 'Hugh Crethar'.

Hugh Crethar, Chair Institutional
Review Board

VITA

Nagesh Ramesh

Candidate for the Degree of

Doctor of Philosophy

Dissertation: DIGITAL TRANSFORMATION: HOW TO BEAT THE HIGH
FAILURE RATE

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Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Business Administration at Oklahoma State University, Stillwater, Oklahoma in May, 2019.

Completed the requirements for the Master of Business Administration in Information Systems Management at Strayer University, Allentown, Pennsylvania in 2013.

Completed the requirements for the Bachelor of Engineering in Mechanical Engineering at Mangalore University, Manipal, Karnataka, India in 2000.

Experience:

Senior Director, CSL Behring, 2015 – Present

Director, IKARIA, 2012 – 2015

Manager, Aesculap, 2009 – 2012

Management Consulting roles, Consulting Firms, 2000-2009