A Decision Support Tool to Improve the Likelihood of Successful Research Project Outcomes

by Andrew C. Merkle

B.S. in Engineering Science and Mechanics, May 1998, Virginia Tech
M.S. in Engineering Mechanics, May 2000, Virginia Tech
M.B.A. in Business Administration, May 2008, University of Maryland, College Park

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Praxis directed by

Timothy Blackburn
Professorial Lecturer of Engineering Management and Systems Engineering

The School of Engineering and Applied Science of The George Washington University certifies that Andrew Charles Merkle has passed the Final Examination for the degree of Doctor of Engineering as of 12 November 2020. This is the final and approved form of the Praxis.

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Andrew C. Merkle

Praxis Research Committee:

Amir Etemadi, Assistant Professor of Engineering and Applied Science, Praxis Co-Director

Timothy Blackburn, Professorial Lecturer of Engineering Management and Systems Engineering, Praxis Co-Director

Aristos Dimitriou, Professorial Lecturer of Engineering Management and Systems Engineering, Committee Member

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Dedication

To my incredible wife, Michelle, and to my wonderful boys, Ethan and Alex. You understood my desire to pursue this degree, patiently endured the time demands and disruptions and provided constant love and support. I am forever grateful. So, what movie are we going to watch tonight?

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Abstract of Praxis

A Decision Support Tool to Improve the Likelihood of Successful Research Project Outcomes

Innovative research projects fail up to 80% of the time, thus wasting resources without achieving project goals. Although some research project failures can be attributed to the inherent risks associated with conducting research, other failures are due to issues in the Innovation Process (IP). The IP describes the framework used to facilitate all phases of a research project, including concept solicitation, selection, management, and transition to application. This Praxis developed a decision support tool (DST) to aid the research portfolio manager (PM) in selecting the optimal IP that will maximize the likelihood of project success. To create this tool, nearly 500 research projects with varying levels of successful outcomes were analyzed to identify the factors critical to project success. Based on the correlation of IP factors and project success, a statistical model was trained and tested. This model was used as the basis of the DST, which enables the PM to input project IP factors and determine the predicted likelihood of project success. Simulated factor modifications demonstrated the DST's ability to inform a PM of improved IP designs resulting in increased likelihood of project success. This validated tool will be especially useful to PMs that work in science and technology organizations and manage innovative research projects.

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List of Symbols

α_j	Y intercept for ordinal logit model
β	Regression coefficient for ordinal logit model
π	Cumulative probability of the response for ordinal logit model
P_j	Probability of project success at level j
$P_{pred\ j}$	Predicted probability of project success at level j for modified factors
H_0	Null hypothesis
X	Independent factors for ordinal logit model
Y	Response variable for ordinal logit model
$e_{(i)}$	Model prediction error
y_i	Measured response
$\hat{y}_i$	Predicted response
n	Number of measured responses in the analyzed dataset
η	Median

List of Acronyms

APL	The Johns Hopkins University Applied Physics Laboratory
DoD	Department of Defense
DST	Decision Support Tool
FAR	Federal Acquisition Regulation
IP	Innovation Process
IRAD	Independent Research and Development
MOR	Mission-Oriented Research
NPD	New Product Development
NMOR	Non-Mission-Oriented Research
PI	Principal Investigator
PM	Portfolio Manager
R&D	Research and Development
TRL	Technology Readiness Level
UARC	University Affiliated Research Center
U.S.	United States

Glossary of Terms

II	Innovation Indicators are independent factors that correlate to the probability of success for an innovative project.
IP	Innovation Process describes the framework used to facilitate all phases of a research project, including idea solicitation, selection, management, and transition to application
IRAD	Independent Research and Development projects are innovative research and development projects focused on future national security technology needs.
PI	Principal Investigator is the lead of a research project
PM	Portfolio Manager oversees a collection of research and development projects
TRL	Technology Readiness Level is a scale used by the US government for estimating technology maturity
UARC	University Affiliated Research Center is a research institution established by the Office of the Secretary of Defense. Developed to ensure that essential engineering and technology capabilities of particular importance to the DoD are maintained

Chapter 1—Introduction

1.1 Background

The United States Department of Defense (DoD) has a long history of investing in research and development (R&D), leading to technological superiority and resulting in benefits to both national security and society. However, the U.S. defense-related R&D fell from 36% of global R&D investments in 1960 to just 3.7% in 2016 (Sargent Jr, Gallo, & Schwartz, 2018). This shift in the global R&D investment landscape threatens to erode the DoD's technological advantage. The DoD must maximize R&D project success rates while not reducing the level of risk tolerance, which is critical to seeking breakthrough technologies and capabilities.

Contractors working for the DoD invest in higher risk, innovative concepts using Independent Research and Development (IRAD). IRAD provides government contractors the opportunity to be reimbursed for costs associated with internally funded R&D projects that are of interest to DoD (Department of Defense, 1999). These projects are intended to accelerate innovative technologies in four areas: (1) basic research, (2) applied research, (3) development, and (4) systems and other concept formulation studies. The IRAD investments must target technologies that will benefit the future of national security.

The Johns Hopkins Applied Physics Laboratory (APL) is a $1.8B not-for-profit University-Affiliated Research Center (UARC) that supports the national security and space missions of the federal government (The Johns Hopkins University Applied Physics Laboratory, 2020). UARCs partner closely with academia, industry and federally funded government laboratories to form the research and development enterprise for the

DoD. As the largest UARC in the U.S. with nearly 8000 staff members, APL invests in IRAD projects to improve and broaden technology in areas of interest to the DoD. Oversight and management of the IRAD investments is delegated to portfolio managers (PMs) that either reside in APL's business units or work across business units on a cross-enterprise innovation initiative. Each PM has worked within their organization to establish their preferred methods to oversee, manage and assess their respective portfolios.

1.2 Research Motivation

R&D investment is critical to the sustainment and future growth of corporations, industries and countries (Becker, 2015; Bilbao-Osorio & Rodríguez-Pose, 2004; Blanco, Gu, & Prieger, 2016; Woo, Kim, & Lim, 2017). These investments intend to foster innovation and ensure future growth and prosperity. Scientific research organizations, including UARCs, invest in R&D to generate new knowledge, explore novel concepts, and invent revolutionary technologies. However, the nature of R&D projects, which are often immature, unproven concepts, are inherently risky and can fail to meet expectations (Castellion & Markham, 2013; Clancy, 1995; Shore, 2005; Stevens & Burley, 1997). Unless these project failures result in, at a minimum, knowledge gain and lessons learned, the projects are a waste of time and money.

R&D project failures are often attributed to the inherent risks associated with conducting research. However, as with any project, failures are also due to issues that occur within the processes that accompany a research project through its life cycle, termed the Innovation Process (IP). The IP describes the framework used to facilitate all phases of a research project, including idea solicitation, selection, management, and

transition to application (Verworn & Herstatt, 2002). No single IP is suited for all projects. Rather, the IP should be designed and implemented on the basis of the organizational strategy and rationale for making the investment.

Scientific research organizations traditionally staff PM roles with engineers and scientists who have demonstrated the ability to successfully conduct innovative research. However, the skills and expertise required to develop an R&D investment strategy and oversee a portfolio of projects are not necessarily acquired through the experience gained from being a researcher. Without these skills, the PM lacks the training or experience to know how to structure an IP that can maximize successful outcomes. Due to the various differences in project environments, even a PM with experience could benefit from assistance in designing an IP to best position a project for success. Therefore, PMs would improve project performance with a better understanding of what IP attributes determine project success and then how to design an IP to maximize the likelihood of success.

This Praxis will develop a decision support tool (DST) to aid the research PM in designing the optimal IP that will maximize the likelihood of project success. To create this tool, nearly 500 APL IRAD projects will be analyzed to identify the factors that were critical to project success. Based on the correlation of IP attributes and project outcomes, a statistical model will subsequently be trained, tested and validated. Once validated, the model will be used to create the tool to inform the design of future projects based on organizational goals, current project factors and the objective of maximizing success. This tool will be especially useful to PMs within R&D organizations supporting the DoD, such as APL, but it will also be useful to PMs within any technical organization.

1.3 Problem Statement

Scientific research organizations experience high project failure rates, thus wasting resources.

As discussed above, research projects can fail for various reasons, one of which is the inherent risk that accompanies pioneering research. This failure is acceptable. However, failures due to a misaligned or poorly executed Innovation Process result in wasted resources.

1.4 Thesis Statement

Through the application of a decision support tool that identifies key success factors, portfolio managers will be informed regarding innovation process design to maximize the likelihood of research project success.

There is no single IP that fits all projects. Key success factors within the IP should be optimized based on alignment with organizational investment objectives. PMs require this tool to examine their existing process and provide guidance in designing future IPs for a project or set of projects.

1.5 Research Objectives

This research is intended to utilize innovation process data collected from five years of IRAD projects to:

- Determine if project success can be predicted by the design of the innovation process.
- Identify those factors that are important in determining the likelihood of project success.

- Create a decision support tool to aid R&D PMs in optimal innovation process design for prospective projects.

1.6 Research Questions and Hypotheses

The Research Questions explore the relationship between the Innovation Process and its impact on project success. Based on that relationship, the Research Questions seek to determine which specific attributes are critical in determining project success and how the alteration of those factors may improve the likelihood of project success.

RQ1: Do Innovation Process (IP) methods impact the likelihood of research project success?

RQ2: Which selected attributes for each stage of the Innovation Process increase the likelihood of a successful project outcome?

RQ3: Are there project parameters that, if altered, will improve the likelihood of success for a project that would otherwise fail?

H1: Five factors impact the likelihood of project success: Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Funding Level.

H2: Implementing changes identified by the decision support tool (DST) will improve all project success ratings to 3 or more.

1.7 Scope of Research

This research examines historical IRAD projects conducted at APL. Nearly 500 projects, conducted from 2016-2019, were selected from four different business units and a cross-enterprise initiative. Factors associated with all phases of the project's IP were

collected from multiple APL databases. The success of each project was determined based on project records and end of project assessments.

This research occurs in three phases: i) model training - develop a statistical model correlating IP attributes (factors) to project success (response), ii) model testing – test the model's ability to predict the likelihood of project success, and iii) model validation and implementation – determine the efficacy of the DST in improving project success. In the first phase, the statistical model employs 70% of the total projects to train a regression model on which IP attributes are statistically significant in predicting project success. In the second phase, the trained and tested statistical model will be tested for performance with the remaining 30% of the project data. The final phase uses the model to create a DST. The DST recommends specific IP modifications for each project and the improvement in project success likelihood is calculated.

1.8 Research Limitations

This research focuses on IRAD projects conducted at APL. Projects included in this effort were diverse in investment objective, application domain, mission focus and scale. These projects also varied in the methods by which they were solicited, selected, managed and transitioned. However, the database has inherent limitations:

- All IRAD projects were conducted at APL. Although the projects were drawn from diverse business units within APL, any impact that fundamental differences in corporate R&D investment principles or constraints might have on the statistical model or the DST guidance cannot be determined from these data.

- All projects were motivated by future impact on the national security and space domains. Although the factors identified as critical for project success are likely to convey into other domains, we cannot make that assessment using these data.
- This dataset includes R&D projects conducted by a scientific research organization. Although the findings likely convey to other project types, such as information technology or construction projects, we cannot conclusively make this determination.
- Project success was assessed within the year the project was conducted. However, research projects often require additional time to realize key indicators of success, including patents, publications and commercialization. As a result, project success may actually increase with re-evaluation at times beyond the conclusion of the actual project period of performance.

1.9 Organization of Praxis

Chapter 2 provides a review of the relevant literature. This chapter describes the importance of innovation for research investments, especially within the DoD, but also stresses the need for strong project management and process. The Innovation Process concept is introduced and innovation indicators that may influence project success are identified. Additionally, metrics for project success are described. Finally, the deficiencies in current tools to support design of an effective IP are examined.

Chapter 3 describes the methods for database development, statistical model training and validation, and deployment of the model for improving project success. Database development includes the determination of project inclusion criteria, attribute

selection and assessment of success. The analysis methods, including ordinal logistic regression, for developing the statistical model are presented. The methods for assessing the impact of IP changes on project success are also described.

Chapter 4 provides the results of the analysis. The statistical model results identify those IP attributes that are critical factors for determining project success. The effect of modifying IP attributes using the DST to improve likelihood of project success is also provided.

Chapter 5 contains the discussion and conclusion. This chapter describes those attributes that determine project success, how modifications of those factors could improve failing projects and prescribes how to deploy this novel DST at APL and within any other organization investing in R&D projects.

Chapter 2—Literature Review

2.1 Introduction

The United States (US) Department of Defense (DOD) is seeking breakthrough technological innovations through investment in research and development (R&D) projects. Although the R&D will be high risk, the process by which it is managed, termed the Innovation Process (IP), does not have to be. As a framework for linking the early stages of research to the ultimate application of technology, the IP is intended to increase the likelihood of innovative project success. This Literature Review will consider the relevant published research that provides the foundation for this Praxis.

Section 2.2 conveys the importance of R&D projects at a global and national scale. The need for innovative R&D is identified as the primary path toward maintaining technological superiority in national security. Independent Research and Development (IRAD) projects are introduced as a DOD means by which to target future innovations.

Section 2.3 provides a definition for innovation and the Innovation Process. The concept of a Defining Innovation, a term created by The Johns Hopkins University Applied Physics Laboratory (APL), is introduced as the ultimate goal of a successful innovation process.

Section 2.4 introduces the challenges with conducting innovative R&D projects. Reasons for project failure are cited.

Section 2.5 introduces the IP and describes the IP models that have been conceptualized, tested and evolved as they keep pace with increased speed and complexity of technology development. The distinction between new product

development and technology development is made and the common IP elements for all IP models are identified.

Section 2.6 describes the Stage-Gate model and the need to customize it within the context of organizational strategy. The technology development version of this model will become the basis for the R&D IP used in this effort.

Section 2.7 defines innovation indicators and reviews the literature indicating important indicators for each stage of the IP.

Section 2.8 examines methods used to evaluate general project success and how they differ with evaluations of R&D projects.

2.2 The Impact of Research and Development Projects

2.2.1 Global Investment Impact

Investment in R&D is critical to the growth and sustainment of countries, industries and corporations. These investments result in the creation of new technologies, capabilities and products which afford political, economic and societal benefits. More than sixty years ago, Robert Solow received a Nobel Prize for indicating that advancements in technology were responsible for more than half of the United States (U.S.) growth in individual productivity per hour (Solow, 1957). More recently, research has shown that state spending on R&D can result in more than 200% return on gross domestic product (Blanco et al., 2016). In Asia, geographic regions supported by R&D investment demonstrate up to four times the growth of those that do not receive human capital or financial capital dedicated to R&D (Woo et al., 2017). In Europe, R&D investment resulted in increased innovation and translation into economic growth (Bilbao-Osorio & Rodríguez-Pose, 2004).

2.2.2 National Security Opportunity for Innovation

The U.S. military superiority is being *challenged by rapid technological advancements and the changing character of war* (Mattis, 2018). The 2018 National Defense Strategy identifies critical elements required to sustain technological superiority, including increased innovation in R&D investments. DOD funds R&D in federal, academic, and industrial laboratories focused on national security innovations. The commitment to long-term research targets revolutionary breakthroughs for both military and civilian applications. These investments train future engineers and scientists and sustain the science and technology workforce. However, despite the importance, U.S. defense-related R&D investments fell from 36% of global R&D investments in 1960 to just 3.7% in 2016 (Sargent Jr et al., 2018). This globalization of research threatens to erode the DoD's technological advantage (Fields & Thomas, 2012).

In 2005 a distinguished committee of American leaders was commissioned by Congress to assess the state of the U.S. science and technology enterprise and the ability to successfully compete, prosper, and be secure in the global landscape (Vest, 2010). The committee identified actionable steps for future changes to policy and investment strategy, among other recommendations. However, they noted that "the only promising avenue for achieving this [latter] outcome….is through *innovation*." This Praxis examines the process that will enable that innovation on a project portfolio or organization scale.

2.2.3 Early stage technology development

The DoD seeks a broad portfolio of high risk, innovative R&D through investment in Independent Research and Development (IRAD). IRAD allows

government contractors the autonomy to initiate and conduct R&D projects of ultimate interest to the DoD and national security missions (Department of Defense, 1999). Furthermore, these investments enable advances in defense-unique fields, attract top talent in the science and engineering workforce, and maintain awareness of fundamental advances in the global research enterprise that could be applied to defense-related problems (Fields & Thomas, 2012). The designated areas for IRAD investment are (1) basic research, (2) applied research, (3) development, and (4) systems and other concept formulation studies (Department of Defense, 1999). IRAD is intended to be an early phase of technology development with an emphasis of vetting initial ideas and demonstrating concepts. If successful, the technology will transition to direct funding by a government sponsor and the R&D emphasis will shift toward addressing mission-driven requirements (Watson, Arnold, & Suter, 2011) or new product development.

2.3 Innovation Defined – Defining Innovation

In 1957 Albert Szent-Györgyi, a Nobel Prize winning biochemist, wrote in his book "Bioenergetics" that "*Research is to see what everybody has seen and think what nobody has thought*" (Szent-Györgyi, 1957). Dr. Szent-Györgyi's quote captures the essence of pursuing innovation through R&D. Although there are many definitions of innovation shaped by perspectives and goals (Satell, 2017; Stone, Rose, Lal, & Shipp, 2008), the focus here is on technological innovation (Garcia & Calantone, 2002). Technological innovation occurs when technical knowledge is transformed into new capabilities, process improvement or economic reality (Bright, 1969; Cantisani, 2006). The process by which this transformation occurs is referred to as the Innovation Process, which will be described in Section 2.5.

Since its founding in 1942, APL was established to mobilize scientific research to address government challenges in national security and space. Throughout its tenure, APL has targeted the creation of *Defining Innovations*, which are the realization of a critical contribution to a critical challenge that forever changes our understanding of what is normal. Similar to traditional definitions of innovation, a defining innovation may involve the invention of a new scientific principle or technology, or it might arise from the ingenious use of existing technologies (The Johns Hopkins University Applied Physics Laboratory, 2020). However, the important differentiator is the realized impact of the innovation. This impact only occurs of the R&D innovation successfully completes the innovation process and the result can be transitioned to further development or application.

2.4 Challenges in Innovation

When R&D projects fail, the cause is not limited to a flaw in the initiating idea or the unsuccessful outcome of a risky technology. Rather, these failures can be the result of poor innovation management intended to mature the technology from idea to application (Cooper, 2006; Van der Panne, Van Beers, & Kleinknecht, 2003). Although organizations recognize the importance of good innovation management and the increased likelihood of project success when performed effectively (Lobo & Samaranayake, 2020), it remains difficult due to the inherent risk of innovative projects and the high failure rates of R&D (Cozijnsen, Vrakking, & van IJzerloo, 2000).

2.4.1 Why Innovative Projects Fail

A review of more than forty published papers examining innovative project failures has revealed four major categories of factors that can impact project success: 1)

Firm-related factors; 2) Project-related factors; 3) Product-related factors and 4) Market-related factors (Van der Panne et al., 2003). The first two categories affect the technological viability of the project whereas the last two categories impact the commercial viability of the project. Since this Praxis is focused on technological innovation through R&D projects and not on the process of introducing new products to market, the second two categories will not be examined further.

Firm-related factors are specific to the organization's ability to foster innovative projects. Factors include the organization's strategy and culture toward innovation, prior experience with innovative projects and the manner in which projects are championed (Van der Panne et al., 2003). Of the factors impacting technological viability of the project, management related issues are the source of 65% of the failures (McManus & Wood-Harper, 2003).

There are two primary project-related factors that impact the technological viability of an innovative project. The first is the complementarity of the organization's resources with the technological viability of the project. Does the organization have the appropriate expertise, infrastructure and support structure in place to successfully execute the project? The second factor is the innovation management style. How does the organization plan for innovative investments, evaluates and selects ideas for investment, staff the project team and oversees the project (Van der Panne et al., 2003)? Technical causal factors, such as inadequate tools and planning, account for 35% of the issues impacting technological viability of the project (McManus & Wood-Harper, 2003).

2.5 The Innovation Process

During his tenure in academia and government, Vannevar Bush recognized and promoted the importance of scientific research to national security. In his report to President Truman in 1945, Bush noted that 'research is the pacemaker of technological progress.'(Bush, 1945). Bush was one of the first to convey the relationship between science and technology development as a linear model, where innovation begins with basic research and then progresses to applied research and development (Godin, 2006). This framework for linking the early stages of research to the maturation and ultimate application of technology has come to be known as the Innovation Process (IP).

Over the last 60 years, a variety of IP models have been conceptualized, tested and refined. Studies have demonstrated that innovation projects are not 'one size fits all' and therefore the process by which they are managed is likely to require customization (Salerno, de Vasconcelos Gomes, da Silva, Bagno, & Freitas, 2015). The models have largely evolved in response to growing complexity and accelerating pace of technology development (Rothwell, 1994) as they seek increased flexibility, speed and efficiency (Eling, Langerak, & Griffin, 2013). It is important to understand the attributes of these models and how they might best align with a certain industry or organizational objectives before employing them.

As an IP model is considered for deployment, awareness of the history of model development provides insights into various model attributes that best support different project types. Model development has been divided into five generations (Rothwell, 1992; Žižlavský, 2013). The first generation occurred in the 1960s and focused on a linear *tech push*, or non-mission-oriented research (NMOR), model. The second

generation included *needs pull*, or mission-oriented research (MOR), models (Globe, Levy, & Schwartz, 1973). In the early 1980s, the third generation was a more generalized version of the push/pull models but it was informed by marketplace considerations throughout the process, known as the coupling model. The fourth generation established the integrated model, which required horizontal integration from early researchers to manufacturing to customers. The fifth generation of IP was defined as the Systems Integration and Networking Model, which introduces information technology methods, such as simulation, into the fourth generation IP to allow for a more efficient process (Žižlavský, 2013). The goal of these later processes was to promote efficiencies and reduction of product development costs (Rothwell, 1994).

IP models from the first three generations are largely similar by their focus on a single managerial process for new product development (Cooper, 1990; Utterback, 1971). These linear processes presume a direct pathway from scientific discovery to technology development to marketplace sales (Rothwell, 1994), which accommodates the general processes used to conduct scientific research. For basic research, the first generation technology push focuses on scientific discovery that is not driven by a targeted mission. Applied research is more closely aligned with the second generation model where the technology development solutions are being pulled toward a specific mission. A more balanced approach, the third generation IP model mostly maintains the serial nature of the first and second generation processes, but it incorporates more interaction and iteration between technology developers and mission owners (Rothwell, 1994). Although there are a number of different versions of these IP models, they include similar phases: idea

generation, idea selection, technology development and technology transition. One of the more widely adopted IP models is the Stage-Gate Process (Cooper, 1990).

2.6 The Stage-Gate Innovation Process

The Stage-Gate IP was largely created based on the observed best practices of successful intrapreneurs when they brought products to market (Cooper, 2014). The goal of establishing Stage-Gate was to provide a process management method to the innovation process (Cooper, 1990). This IP is now one of the most widely employed innovation processes (Ettlie & Elsenbach, 2007) and surveys conducted by the process originators have found as many as 75% of the top performing companies surveyed have adopted some form of the IP (Cooper, 2014; Cooper & Edgett, 2012). Additionally, research organizations within the federal government, including the Department of Energy (DOE) and the Department of Defense (DOD) also use a version of the Stage-Gate IP (Bonvillian & Van Atta, 2011; Jing, Zenghua, & Xuejun, 2020; Ruegg & Jordan, 2007).

In its initial conceptualization, the stage-gate process had five stages (Figure 3-1). Each stage represented a major phase in the innovation process for new product development. The initial design included: 1) Preliminary Idea Assessment, 2) Business Case Preparation, 3) Development, 4) Testing and Validation and 5) Production and Launch (Cooper, 1990). For a project to advance to the next stage, it must satisfy a set of criteria as defined by the process owner, termed the ‘gate’ (Cooper, 2008).

2.6.1 Innovation Process Customization

Although the Stage-Gate process provides a well-defined framework for managing innovation projects, recent studies have demonstrated that innovation processes

are not *one size fits all*. Rather, the IP model should be tailored to organizational attributes (e.g, small vs large company), investment goals (e.g., new product development vs. basic research) and characteristics of the specific innovation project (e.g., radical vs. evolutionary) (Rice, OConnor, & Pierantozzi, 2008; Salerno et al., 2015), among other attributes. Since its original inception, the stage-gate process has gone through revisions to incorporate a front-end discovery process (Figure 3-1), agile methods, spiral development, and scalable processes. These additions enable innovation process designs that can now accommodate non-linear, dynamic projects that require iterations and flexibility (Cooper, 2014; Cooper & Sommer, 2016).

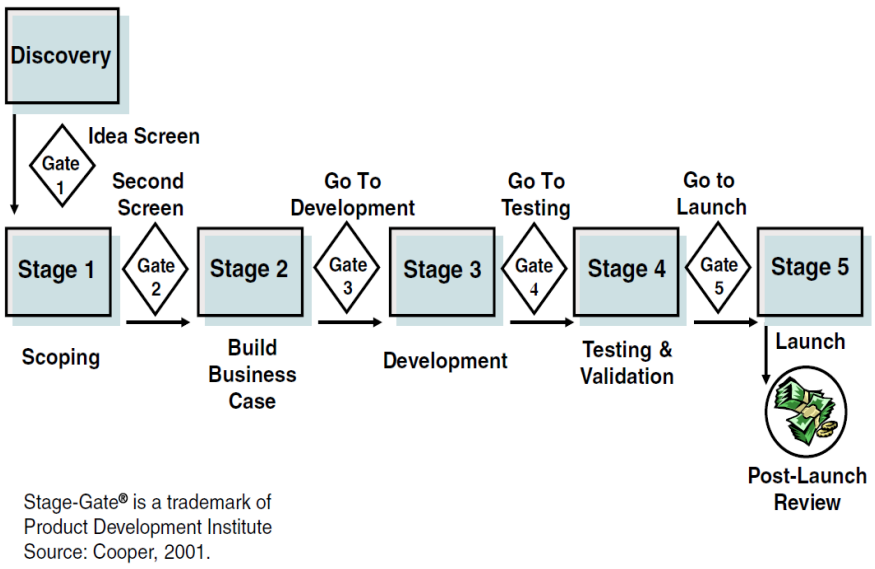

Figure 2-1. The notional stage-gate process (Cooper & Kleinschmidt, 2001).

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2.6.2 Stage-Gate IP for Technology Development

The initial Stage-Gate IP was developed with a focus on new product development. However, instead of a focus on new product launch, scientific R&D projects focus more on technology development and maturation with the end goal as new

knowledge or capabilities. This new knowledge or capability, once matured, could result in new products. To accommodate technology development, the Stage-Gate process was modified to include a two-stage, three-gate process (Cooper, Edgett, & Kleinschmidt, 2002) as a precursor to the new product development process (Figure 3-2). The two stages focus on the conceptualization and execution of the research, respectively.

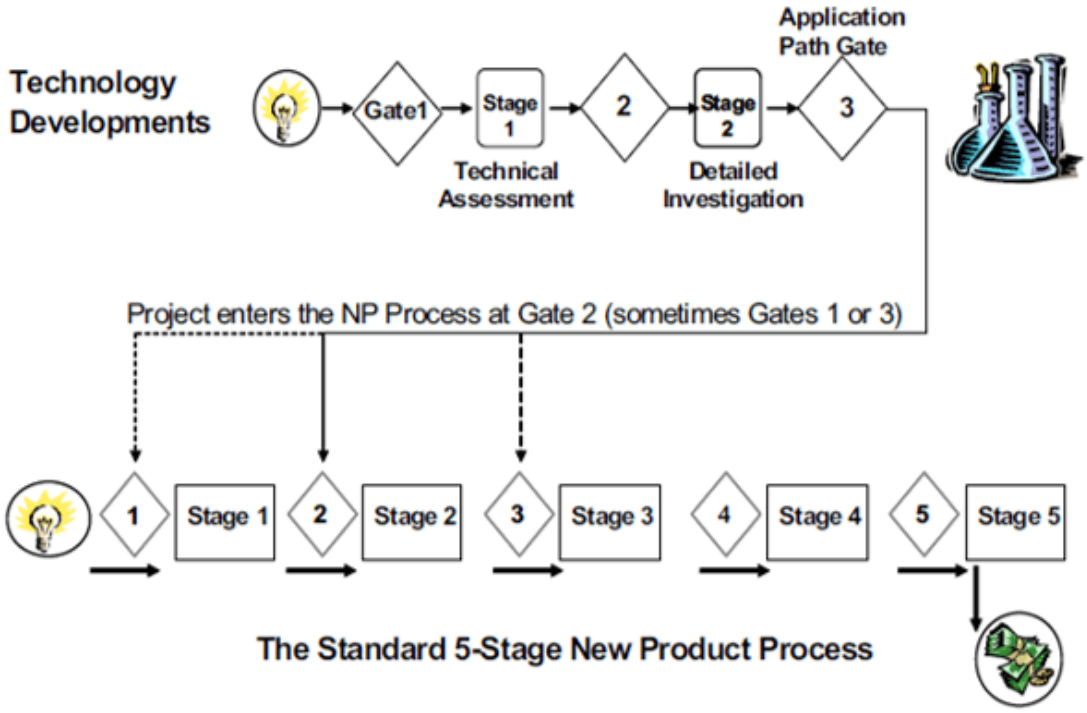

Figure 2-2. Stage-Gate technology development process for research projects (Cooper et al., 2002).

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2.7 Innovation Indicators

To customize an IP that will best suit organizational objectives, maximize innovation and increase the likelihood of project success, it is important to first understand which factors at each stage of the IP actually affect project success. When identified and correlated to project success, these factors are termed innovation indicators. These indicators are elements that, when applied during the innovation

process, can increase a project's chances of being successful (Joslin, 2019). If the magnitude of the impact of each innovation indicator for each stage is known, the stages that should be included in an R&D IP will be apparent. Furthermore, knowing these factors informs the portfolio manager (PM) as to any management actions to take or metrics to monitor as they seek to maximize innovation and target a successful project outcomes.

The literature has largely examined two separate portions of the IP pertaining to new product development (NPD) innovation indicators: the front-end stages that occur prior to a decision to fund a project and then the period after a product makes it to market (Dziallas & Blind, 2019). The front-end of the IP is similar for NPD and R&D projects, which includes the idea solicitation, selection, and resource allocation for innovative concepts (Khurana & Rosenthal, 1998; J. Kim & Wilemon, 2002; Reid & De Brentani, 2004). The post-launch stages differ between NPD and R&D. In NPD, the focus is on how well the product demonstrates improvement over existing products, customer ease of use and other product adoption factors (Dziallas & Blind, 2019). For R&D, projects target knowledge products or new capabilities instead of product launch. Therefore, the later stages of the R&D IP is focused on PM oversight of project progress and technology maturation for transition.

For leading innovation indicators that occur during the project lifecycle and are predictive of project success, the PM can actively modify them with the goal of maximizing project success. However, the stage in which these modifications occur, as well as the nature of the modification, will determine the magnitude of the impact.

Various innovation indicators have been identified in the literature and will be considered here within the appropriate innovation process stages.

2.7.1 Idea Solicitation

The first stage of the R&D IP focuses on both the solicitation and subsequent generation of ideas. Scientific R&D is often initiated with a request that innovative concepts or ideas be proposed to the management overseeing the solicitation. This first stage, initiated by management, requires a clear definition of the targeted challenge or research focus area, which is important to initiate a creative response (Arreola & Reiter-Palmon, 2016). Researchers intending to respond to the solicitation then engage in the idea generation process.

Most studies evaluating innovation indicators have focused on the later stages of the IP. However, the process indicators on the front end of the IP are very important for properly initiating the research process and for research management to clearly signal organizational priorities (Dziallas & Blind, 2019). These processes should align with the organizational goals, but they should not be overly structured if a goal of the process is to seek radical innovation (Khurana & Rosenthal, 1998). Successful R&D relies heavily on great ideas. These ideas originate from motivated researchers willing to develop and share proprietary ideas through the proposal process (Azoulay, Fuchs, Goldstein, & Kearney, 2019; Fuchs, 2010). It is the goal of the solicitation to bolster the quantity of quality proposals submitted by clearly communicating the organizational objectives and areas of interest, prescribing submission requirements and revealing proposal review criteria. As part of the solicitation, the process may include an information session or other open, collaborative engagements to facilitate feedback between the funding

organization and the prospective proposers as well as create introductions across organizations that may benefit from joint ideation and feedback (Velamuri, Schneckenberg, Haller, & Moeslein, 2017). The solicitation should also allow for diverse idea generation processes (e.g., design thinking, TRIZ, brainstorming, etc.) to enable a diversity of concepts to form for different types of opportunities (S.-K. Kim, 2014). Lastly, the time it takes to complete the solicitation process (S.-K. Kim, 2014) is also an important indicator as it limits the complexity and depth of the responses if too short and can inhibit any momentum created by the initial solicitation if the response time is too long.

2.7.2 Proposal Selection and Resourcing

The methods by which proposed ideas are evaluated is a heavily studied stage in the innovation process, likely due to the importance of the decision made to commit resources. The effective investment into successful R&D projects is critical to the future of an organization. There are often more strong ideas than resources by which to fund them, thus creating a competitive environment. When a project is selected it indicates that the project's strategy alignment, technical approach and potential future impact are well understood and that the benefit of a successful project outweighs the risks. However, even if we can predict that an R&D project will achieve its technical objectives, we cannot be certain of how the output will transition to the targeted community (Henriksen & Traynor, 1999). Therefore, formulating selection methods that can best inform the likelihood of project success are essential.

Through decades of research, various R&D project selection methods have been developed. These methods include unstructured peer review, customized scoring

methods, mathematical programming, cost-benefit models, and decision analysis (Henriksen & Traynor, 1999). However, no single selection model has been widely adopted. The optimal model must satisfy three organizational needs: 1) align criteria with corporate strategy; 2) weigh benefits and risks of the project; and 3) reconcile different stakeholder interests (Meade & Presley, 2002). With differences in organizational goals, risk tolerance, stakeholder perspectives, etc., each organization needs to choose a model. Based on their differences, the optimal selection method will be different.

Since no single selection method can account for the perspective and considerations of all R&D investment stakeholders, another approach to seek the optimal investment portfolio is to use competing selection methods concurrently and determine aggregate scoring to determine which projects emerge as top candidates (J. Kim & Wilemon, 2002). For example, project selection based on senior leader scoring will ensure alignment with strategy and commitment of resources (Mumford & Mulhearn, 2019). Mathematical programming models will provide objective measures. Crowdsourcing selection has been shown to reduce experience and gender bias while embracing risk and promoting transparency (Sauermann, Franzoni, & Shafi, 2019). Scientific peer review will confirm scientific validity of the proposed approach. The tradeoff is that the use of too many models can become confusing or overly burdensome, uneconomical for small R&D investments, and inefficient for agile processes.

Management participation in and support of the selection process is a discriminator between project success and failure (Dougherty & Hardy, 1996; J. Kim & Wilemon, 2002; Mumford & Mulhearn, 2019). For R&D projects, this is especially motivating to researchers as it demonstrates organizational commitment to making

investment decisions based on unproven ideas or early stage concepts. Management participation in the project evaluation stage assures that project selections will align with strategic objectives while also maximizing innovation. Additionally, management will be vested in appropriately resourcing selected projects, and maintain the continued investment, if they have actively joined in the evaluation process.

Proposal feedback is a critical component at the conclusion of the selection stage. For those projects that are selected, the feedback helps to refine the selected concept and address any deficiencies identified during the selection process. For those projects not selected, which is often the majority, the feedback helps to motivate researchers to maintain the flow of new ideas, provides direct guidance on how to improve the idea, and increases the likelihood that they will submit again in the future (Piezunka & Dahlander, 2019). However, the feedback must be encouraging and coherent with strategy and priorities or it will demotivate the researcher (Hartmann, Laubengaier, & Foerstl, 2019). Portfolio managers should play an active role in providing the feedback (Mumford & Mulhearn, 2019).

2.7.3 Project Execution Phase

Innovation indicators associated with the process of executing the R&D project can be grouped into two principal categories: culture and people. Cultural indicators of innovation include how an organization approaches project governance and promotes collaboration. People indicators include the attributes of project managers and the project team.

Project champions play an important role in the conceptualization and execution of an innovative R&D project. The combination of their enthusiasm, drive and technical

competence can inspire an organization to embrace a broad vision, sustain investment, and compel the team to take on risk required to seek a successful innovation (Chandy & Tellis, 1998; Howell & Higgins, 1990; Rutten, Doree, & Halman, 2019). Champions must lead both the project and the people to ensure success (Mumford & Mulhearn, 2019). Furthermore, the more radical the project the more critical the presence of a champion is to increase the likelihood of success (Lee & Na, 1994).

The ability of multi-disciplinary teams to solve tough challenges with innovative solutions has been the focus of recent research. Specific dimensions of team diversity have been correlated to enhanced R&D innovation. For example, diversifying the problem-solving approaches used by team members, either by changing the composition or training them in alternative styles, promotes divergent thinking and novel solutions (Post, De Lia, DiTomaso, Tirpak, & Borwankar, 2009). In a study examining thirty years of research on team dynamics, job-relevant diversity, such as technical discipline, was correlated with innovation (Hülsheger, Anderson, & Salgado, 2009). In the same study, an increase in team size also was positively correlated to innovation on difficult tasks due to the expanded diversity of knowledge and skills.

Project governance, which is the "use of systems, structures of authority, and processes to allocate resources and coordinate or control activity in a project" (Pinto, 2014), has been examined as a factor for project success (Joslin & Müller, 2016b) . For innovative R&D projects, which tend to be smaller investments, the governance structure must find a balance between being process-focused and completely unstructured (Turner & Müller, 2004). Governance during project execution includes the structure and scope of the project review process. For example, are reviews held infrequently as simple status

update or are they held on a more regular basis and include thorough technical exchanges and progress assessments? This process is important as these reviews provide opportunity for progress assessment, course correction, and dissemination of recent results.

2.8 Measuring R&D Project Success

Measuring the success of R&D projects is a difficult challenge but it is essential if the benefit of the investment and the knowledge of how to improve future investments is to be known. Success itself must first be defined, which often is a function of the organizational strategy and goals. Then, the factors that indicate success must be identified and available for measurement. Finally, if the ultimate goal of measuring success is to be able to improve upon it, then the factors must be able to be modified through actions taken by the PM or others involved in the project.

Simply evaluating project scope, cost and performance at the conclusion of a project is no longer an adequate approach to assessing success (Jugdev & Moller, 2006). Rather, success is now recognized as a multidimensional construct. The evaluation of any project may include a temporal aspect, which includes short-term project management success and an evaluation of the long-term impact (Jugdev, Thomas, & Delisle, 2001). Success can also be defined on the basis of perceived value proposition from those stakeholders responsible for evaluating it, with three major dimensions of 1) achieving the project plan, 2) realizing the business case, and 3) valuing the investment (Zwikael & Meredith, 2019). Another success definition seemingly combines aspects of the prior two methods as it lays out five criteria: project efficiency, organizational benefits, project impact, stakeholder satisfaction and future potential (Joslin & Müller, 2016a). In contrast, another model suggested that other than project efficiency (cost, schedule) and

effectiveness (completed objectives) there are no common measures of success because they are based on organizational differences (e.g., public vs private) and strategy.

R&D projects often use both leading and lagging indicators as metrics of project success (Darrin & Krill, 2016). Lagging indicators are those that occur after project completion and are therefore outcome-based. For research projects, these indicators could include patents, publications, the impact of the innovation itself, etc. Although lagging indicators may provide a reasonable assessment of project success, management has less direct control over these factors and must wait until the conclusion of a project or beyond to gain insight into performance. Leading indicators are prediction-based and can be measured while the project is active. Therefore, management could monitor these indicators and introduce changes as needed to improve project likelihood of success. For example, team technical diversity (Post et al., 2009) and the number of issues identified and resolved via technical reviews can be leading indicators of project success (Zheng et al., 2019).

According to a review spanning nearly 40 years of R&D performance evaluation research, the most successful approach to measuring effectiveness combines objective and subjective methods (Werner & Souder, 1997). This approach results in a reduction of bias and provides balance while allowing for flexible methods that accommodate factors that change in their relative importance through the stages of the research. Regardless, because R&D is fundamentally uncertain, the measurement of success will always remain imperfect and organizations should find a method or methods that best suit their goals.

Chapter 3—Methodology

3.1 Introduction

The Johns Hopkins University Applied Physics Laboratory's investment in early-stage, innovative research and development (R&D) projects focuses on addressing future national security technology capabilities. The intent of Independent Research and Development (IRAD) investments is to maximize innovation while seeking breakthrough technologies through embracing technical risk. This praxis will examine how the potentially competing forces of maximizing both project success and technical risk can be accomplished through the effective design of the innovation process (IP). This chapter provides the methods used to train and test a statistical model that describes the relationship between IP factors and the likelihood of project success. Furthermore, the methods required to validate the model and implement that model as the basis for an IP Decision Support Tool (DST) are described.

Section 3.2 defines standard stages and gates for APL IRAD IP. Innovation indicators, which are the independent factors to be correlated to project success, are identified for each stage of the IP.

Section 3.3 describes the methods used to construct the IRAD project database. A set of inclusion and exclusion criteria were applied to the initial database to identify the projects that should be included in the model.

Section 3.4 introduces the rating scheme for project success and describes the methods for establishing the ratings.

Section 3.5 describes the processes to address Research Hypothesis 1 (H1). The data analysis methods for training and testing the model, which seeks correlations of

innovation indicators with project success, are described. The processes for confirming model assumptions are also described.

Section 3.6 provides the methods for investigating Research Hypothesis 2 (H2). The process for validating model ability to improve project success through factor modification is provided. The implementation of this model into a DST is described.

3.2 Innovation Process: Factor Identification and Data Collection Methods

As introduced in Chapter 2, the IP describes the framework used to facilitate all phases of an innovative research project. The IP must first be defined and associated independent factors need to be determined before the database can be constructed. Once these steps are taken, then it will be apparent which data must be collected for inclusion in the statistical model development.

APL IRAD investment resources are allocated to, and managed by, business units, termed mission areas, and a cross-enterprise innovation initiative named Project Catalyst. These thirteen organizations are granted autonomy in determining how to identify, resource and oversee a portfolio of innovative projects. The investment strategy is informed by organizational objectives and aligned with the organization's priorities.

Although APL IRAD investment is distributed amongst multiple organizations, there are commonalities in how these organizations approach their respective IPs. Each organization has an IRAD IP with three major stages: Solicit, Select, and Manage (Figure 3-1). Each of these stages is followed by a gate with a criteria that must be met to permit progression to the next stage. The factors within each stage are consistent for all projects, but the specific levels within those factors are often different. The Portfolio Manager (PM), as appointed by each organization, oversees the selection of factor levels, thus

leading to the IP design. The IP stages and associated factors that will inform the process and project data collection are described below.

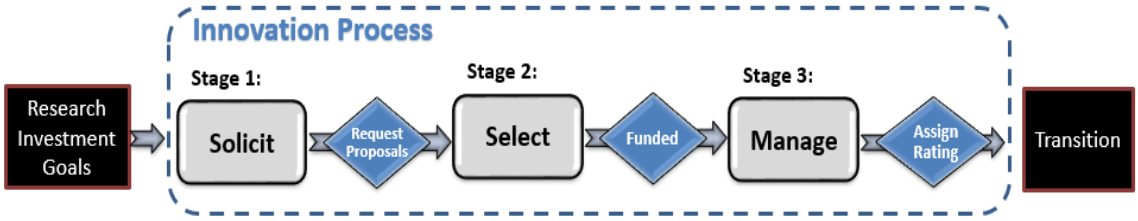


Figure 3-1. Three-Stage Innovation Process describing APL IRAD projects.

Innovation indicators are factors that correlate to the probability of success for an innovative project. As introduced in Chapter 2, research and development (R&D) projects often use both leading and lagging innovation indicators. Leading indicators occur during the project lifecycle and are predictive of project success. They can be actively modified during the IP of a current project or in anticipation of future projects to improve the likelihood of success. Lagging indicators occur after project completion and are therefore outcome-based. For this reason, lagging indicators cannot be actively modified to improve a project. The intent of this Praxis is to enable the PM to modify the IP to maximize likelihood of project success. Therefore, only leading innovation indicators that can be modified by the PM will be considered in this research. Each IP stage will be examined below and the candidate factors identified.

3.2.1 Stage 1: Solicit

Each organization initiates their annual IRAD IP with a solicitation for project proposals. The organization leadership pre-determines an investment strategy and then publishes a solicitation that communicates the organization's strategic objectives, research investment priorities and the process by which proposals should be submitted. The factors associated with the solicitation process are provided in Table 3-1. These factors are routine components of the solicitation process and are not specific to any single organization.

Although the factors consistently exist for all projects, the factor levels differ. Table 3-1 identifies levels for each factor that are either available options or commonly chosen selections made by the organization leadership when designing their IP. To determine the organizational IP factor levels for their R&D portfolio, the organization's strategy and yearly IRAD proposal solicitations were collected and reviewed. For example, mission areas focused on mission-oriented research (MOR) predominantly invest in IRAD projects that are mission driven. Whereas, Project Catalyst has an open solicitation and is interested in both MOR and non-mission oriented research (NMOR). As another example, there are various formats for submitting proposal ideas for consideration (e.g., presentation, written proposals, etc.). The method selected by an organization is described within their proposal solicitation documents.

Table 3-1. Factors and Levels for Stage 1 of the APL IP Process.

Stage 1: Solicit		
Factors	***Level***	***Description***
Objective: *defines organizational motivation for project*	**1**	**Mission driven**
	2	**Technology driven**
	3	**Open**
Response Time: *duration of solicitation response*	**1**	**< 1 month to formulate proposal**
	2	**> 1 month to formulate proposal**
Solicitation Author: *Author of the proposal solicitation*	**1**	**Subject matter expert(s)**
	2	**Management (program or line)**
	3	**Process facilitators**
Proposal Format: *Required proposal submission format*	**1**	**Slide content**
	2	**Written summary**
	3	**Oral Presentation**
	4	**Combination requiring multiple response phases**
Information Session: *Organizational assistance with proposal formation*	**1**	**Yes**
	2	**No**
Revision Process: *Allowance for and nature of proposal revisions*	**1**	**Single submission; no formal feedback**
	2	**Single submission; pre-proposal feedback provided**
	3	**Multiple submissions; oral or written feedback provided**
Feedback Style: *Manner in which feedback is delivered*	**1**	**Written feedback**
	2	**Verbal feedback**
	3	**Crowdsourced feedback**
Feedback Author: *Participants contributing to creating and providing feedback to Principal Investigator*	**1**	**Crowdsource**
	2	**Mission management**
	3	**Technical management**
	4	**Mission and Technical management**
Feedback Cycles: *Nature of organizational feedback provided*	**1**	**0**
	2	**1**
	3	**2 or more**
Data Sources: *Annual mission area proposal solicitations; Project Catalyst proposal solicitations; Organization strategies*		

3.2.2 Stage 2: Select

The second stage of the IRAD IP is focused on proposal selection. The selection process includes factors that define the evaluation of the submitted proposals and the decision to resource them (Table 3-2). The proposal evaluation process can range from a single round of assessments to a series of reviews which allow for proposal feedback and resubmission. The proposal submissions can take the form of a written proposal, briefings or a combination of both. The submissions will propose scope, cost and targeted outcomes. The review committee, which may include representatives from program management, technical management, some combination of both or the selections could be crowdsourced and performed by peers, evaluates the proposal. The resourcing decision is based on the leadership's assessment of the proposed investment, the ability of the research team to successfully execute the scope, the duration and other considerations. Any additional programmatic or technical risk are also assessed, to include facility and equipment availability as well as staff availability to commit to the project.

Table 3-2. Factors and Levels for Stage 2 of the APL IP Process.

Stage 2: Select		
Factors	***Level***	***Description***
Selection Method: *Responsible for making project funding decision*	1	Crowdsourced
	2	Subject Matter Expert(s)
	3	Management
	4	Combination (Management and Subject Matter Expert)
Proposed Cost: *Project cost as originally proposed by the PI*	1	$7-$49k
	2	$50 - $99k
	3	$100 - $249k
	4	$250 - $749k
	5	> $749k
Partnering Funding Organization(s) : *Number of organizations partnering to fund project*	1	Single funding organization
	2	Multiple funding organizations
Period of Performance: *Duration of the project*	1	0-6 month
	2	6-12 months
Tech Readiness Level: *Assessment of project technology maturity*	1	TRL 1 – Basic principles
	2	TRL 2 – Tech concept / Application formulated
	3	TRL 3 – Analytical and experimental studies
	4	TRL 4 – Validation in lab environment
	5	TRL 5+ – Validation/Prototype in relevant environment
Proposal Reviewers: *Role of those conducting the reviews*	1	Technical
	2	Mission
	3	Technical + Mission
	4	Peer
IRAD Category: *Formal designation of the investment category as defined by the DoD*	1	Basic Research
	2	Applied Research
	3	Development
	4	Systems Concepts and Other Studies
Data Sources: *APL IRAD Management System; Proposal solicitations*		

The primary data sources for this stage were the proposal solicitation documents and the APL IRAD Management System (IMS). The solicitation documents provided details regarding the approach to the review process. The IMS, an APL IRAD project archival database, provided all of the associated details for the project itself. For example, the proposed cost, the duration, and the IRAD investment category can be obtained through the database. These data were output from the database using queries for all IRAD projects from 2016 to 2019.

3.2.3 Stage 3: Manage

The final stage of the IRAD IP includes all aspects of management oversight during project execution. Stage 3 IP factors include process factors and project factors that may impact likelihood of project success. For example, process factors include the frequency of progress reviews, the focus of those reviews and who is conducting them. Based on these review outcomes, the PM could enhance the review process, increase (or decrease) investment, change team composition or modify any other factor that could influence likelihood of success. The table of process factors are included in Table 3-3 and the project factors are in Table 3-4. The process factor data for the management stage was collected based on published organizational processes, observed processes employed within each organization and from historical data provided by the PM.

The project factors were collected from multiple sources. The APL IMS database was queried to determine project details including the name of the Principal Investigator (PI) and the unique IRAD project identifier code (PIC). To gain additional data regarding the PI, the PI's name was cross-referenced to the APL staff database to extract additional information regarding their technical background, highest degree achieved and staffing

classification. To gain additional information regarding the project team composition, the PIC was cross-referenced with the APL labor tracking database to determine what other staff members worked on the project. Similar to the analysis performed for the PI, relevant staff data was then extracted to determine the technical backgrounds, degrees and seniority for each team member.

Table 3-3. Process Factors and Levels for Stage 3 of the APL IP Process.

Stage 3: Manage (Process Factors)		
Factor	***Level***	***Description***
Review Team: *Team responsible for monitoring project progress*	**1**	**Peer**
	2	**Technical Management**
	3	**Mission Management**
	4	**Technical + Mission Management**
Review Frequency: *Frequency of reviews held by the Review Team*	**1**	**Weekly**
	2	**Monthly**
	3	**Quarterly**
	4	**Semi-annually**
	5	**Annually**
Oversight: *Measure of active involvement and nature of the reviews conducted by the Review Team*	**1**	**No reviews or active oversight**
	2	**Single, final review**
	3	**Multiple reviews; progress assessment**
	4	**Multiple reviews; project and technical direction**
Data Sources: *Published organizational processes, observed process implementation or PM reference*		

Table 3-4. Project Factors and Levels for Stage 3 of the APL IP Process.

Stage 3: Manage (Project Factors)		
Factor	***Level***	***Description***
PI Professional Experience: *Years of professional experience* **PI APL Experience:** *Years of professional experience at APL*	**1**	**0-5 years**
	2	**5-10 years**
	3	**10-20 years**
	4	**>20 years**
PI IRAD Project Experience: *Number of prior IRAD projects led, beginning in 2015*	**1**	**0 prior IRAD projects led**
	2	**1-3 prior IRAD projects led**
	3	**>3 prior IRAD projects led**
PI Organization: *Each organization given unique identifier*	**1-6**	**One level for each organization**
PI – Organization Alignment: *Assess if the PI is from the funding organization*	**1**	**Funding org. same as PI org.**
	2	**Funding org. different than PI org.**
PI Classification: *APL staff classification for the PI*	**1**	**Associate**
	2	**Senior**
	3	**Principal**
PI Degree Level: *Highest degree for the PI*	**1**	**Bachelors**
	2	**Masters**
	3	**Doctorate**
Team Unique Majors: *A measure of team composition technical diversity*	**1**	**One unique technical discipline**
	2	**Two unique technical disciplines**
	3	**Three unique technical disciplines**
	4	**>Three unique technical disciplines**
Team Master's Degrees: *Number of team members with Master's degrees* **Team Doctoral Degrees:** *Number of team members with Doctoral degrees*	**1**	**None**
	2	**1**
	3	**2**
	4	**> 2**
Team Missing: *Number of proposed team members that never actually worked on the project*	**1**	**None**
	2	**1-2**
	3	**3-4**
	4	**> 4**
Team Size Delta: *Changes required to go from proposed team to actual team (Levenshtein distance)*	**1**	**0-2**
	2	**3-5**
	3	**6-8**
	4	**> 8**
Actual Team Size: *Number of staff that charged >0.1 staff months to the project*	**1**	**0-3**
	2	**4-7**
	3	**8-10**
	4	**>10**
Underfunded: *Determines if PI was funded proposed amount*	**1**	**True = > 0.95 * Proposed Funds**
	2	**False < 0.95 * Proposed Funds**
Expenditures: *Amount of funds actually spent through the course of the project*	**1**	**$7-$49k**
	2	**$50 - $99k**
	3	**$100 - $249k**
	4	**$249 - $749k**
	5	**> $749k**
Data Sources: *APL IRAD Management System (IMS) database, Staff database, Labor tracking database*		

3.3 Establishing the Project Dataset

This research is focused on determining which IP factors correlate to the success of innovative R&D projects. To do this, a curated database of the factors associated with recent (2016-2019) IRAD projects must be established. To determine which projects are suitable for this analysis, a set of inclusion and exclusion criteria were devised. The goal was to maximize the number of projects admitted to this research, while removing any projects with incomplete, incorrect, or unverifiable data. The criteria were created and applied at two levels: the organization level and the project level. The criteria are introduced and described below.

3.3.1 Inclusion Criteria: Organization Level

Although each organization being considered in this study (12 mission areas and Project Catalyst) have similar IRAD investment objectives, they maintain distinct processes. If differing processes prevent data from being directly compared across organizations, then those differences must be identified and evaluated to determine if an organization should be included in this analysis. The inclusion of varying IP designs will aid in the development of a robust statistical model. However, any processes that render the data incompatible with other organizations could pollute the larger dataset, skew the analysis or weaken the ability to recognize statistically significant factors. Therefore, organization level inclusion criteria were established and applied. These inclusion criteria are included in Table 3-5.

Table 3-5. Organization Level Inclusion Criteria.

Inclusion Criteria	*Description*
Non-sensitive Project Information	Project information must be eligible for inclusion in the analysis and able to be publicly released.
Accessible Project Records	The organization must use the central APL database to record data for each individual project.
Portfolio Oversight Continuity	Historical project ratings and process factors should be available and accessible either through published documentation or directly from the Portfolio Manager.
Investment Continuity	Organizations must have a minimum of three years of IRAD investment records, beginning in 2017, with a preference of 5 years of records.

3.3.2 Exclusion Criteria: Project Level

After determining which organizations would be included in the analysis, project level exclusion criteria were applied. These criteria were applied to each project to ensure data completeness, quality assurance and interpretability. Each project data record was inspected manually. If the criteria in Table 3-6 were not met, then the entire project data record was excluded.

Table 3-6. Project Level Exclusion Criteria.

Exclusion Criteria	*Description*
Incomplete Data Records	Missing data regarding project descriptions, factors or assessment.
Project Size	Small projects (<$7k) are not subjected to the IP stages. Large projects (>$1M) are often funded due to strategic initiatives and are not subjected to the traditional IP stages.
Unverifiable or Unexplainable Data	Data field cannot be explained or verified, either due to database entry error or other causes.

3.4 Response: IRAD Success Rating

Determining the success of an R&D project depends upon stakeholder perspective and the definition of success. This research is focused on the ability of management to increase the probability of project success through changes to the IP of R&D projects. Therefore, success is defined from a management perspective and based upon management-perceived value. With the focus on early R&D projects with game-changing potential, success was based on two key components: the ability of the project to develop new knowledge, technologies or capabilities and the likelihood that the project transitions to future investment.

The success ratings for each IRAD category are defined in Table 3-7. A five point scale was chosen based on two reasons. First, studies have demonstrated that reliability for discrimination between levels increases beyond a four point scale (Preston & Colman, 2000). Second, there is a practical limit to the discrete levels that can be used to resolve differences in project success.

To determine the ratings, both historical assessments and supporting data were collected. Historical assessments were provided by the organization that oversaw the project, which included a combination of technical and mission managers. Supporting data included compiled records of knowledge products, such as publications and intellectual property disclosures. These data were collected by cross referencing the PIC with two APL databases. Associated publications were available from the external release archival database. Intellectual property disclosures were available from the technology transfer database. In addition, the IMS records were reviewed for progress assessments.

Table 3-7. IRAD Success Rating Scheme

Ordinal Level	Basic Research	Applied Research	Development	Systems and Other Concept Formulation Studies
1	Effort not completed or stopped	Effort not completed or stopped	Effort not completed or stopped	Effort not completed or stopped
2	Effort completed; no novel findings; no intellectual property; no transition	Effort completed; maturity unchanged; no further investment planned; no transition	Initial prototype created, but did not successfully perform; no further investment; no transition	Initial attempt to conceptualize new system or modify existing system; development remains but further investment not likely
3	Effort completed; some novel findings; no intellectual property or knowledge products; potential to transition but not certain	Effort completed; maturity unchanged; further investment potential but not clear	Initial prototype created, but development remains; further investment potential but not clear	Initial attempt to conceptualize new system or modify existing system; promising initial results; further investment potential but not clear
4	Effort completed; novel findings; IP and/or knowledge products highly likely; further investment likely	Effort completed; maturity increased (TRL +1); further investment likely	Initial prototype created and successfully demonstrated; further investment likely	New or modified system analysis complete. Results indicate new/modified system benefits that can be realized; further investment very likely.
5	Effort completed; novel findings; IP and/or knowledge products highly likely; created new areas of sponsored research; further investment definite	Effort completed; maturity changed (TRL>+1); further investment definite or transition to government funding	Initial prototype created and successfully demonstrated; exceeded expectations; further investment definite	New or modified system demonstrated. Results indicate initial benefits; further investment definite.

3.5 Data Analysis Method

A multi-step data analysis process was employed to evaluate the two research hypotheses (H1 and H2). The initial analysis step was focused on the training and testing of a statistical model relating the dependent response variable (Project Rating) and independent IP factors (innovation indicators). The second step sought to validate the

model through an evaluation of the model's ability to demonstrate an increase in project performance through suggested IP modifications. This section will provide the associated methods used to conduct this data analysis for each research hypothesis.

3.5.1 H1: Regression Model Development Approach

H1: Five factors impact the likelihood of project success: Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Funding Level.

Project success is the dependent response variable and is measured on an ordinal scale. Considering the ordinal nature of these data, Ordinal Logistic Regression (OLR) was selected as the regression analysis method to build a model that determines which innovation indicators are statistically significant predictors of project success. Ordinal logistic regression with proportional odds fits a model for cumulative logits with the following form:

$$logit(Y_j) = \ln\left(\frac{\pi_j(x)}{1-\pi_j(x)}\right) = \alpha_j + \left(\beta_1 X_1 + \beta_2 X_2 + \cdots \beta_p X_p\right) \quad (3.1)$$

Where Y is the response variable, j is the number of categories for the response variable (beginning with 1 and a maximum of J), π is the probability of the response, α is the Y intercept, β are the regression coefficients, X are the factors and p are the number of statistically significant factors that are included in the model. The cumulative probability for a specific response level (π_j) to occur can be determined by:

$$\pi_j = \mathrm{P}(\mathrm{Y} \leq \mathrm{j} \mid X_1 = x_1, X_2 = x_2, \ldots X_p = x_p) = \frac{e^{\alpha+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}}{1+e^{\alpha+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}} \quad (3.2)$$

The cumulative probability at the final level (J) is 1. Considering proportional odds, the individual probability for a selected response level is determined by computing the

cumulative probability at the level of interest and subtracting the cumulative probability of the prior level, as shown in Eqn. 3.3.

$$\mathrm{P}(\mathrm{Y} = \mathrm{j} \mid x_1, x_2, \ldots x_p) \;=\; \mathrm{P}(\mathrm{Y} \leq \mathrm{j} \mid x_1, x_2, \ldots x_p) - \mathrm{P}(\mathrm{Y} \leq \mathrm{j} - 1 \mid x_1, x_2, \ldots x_p) \quad (3.3)$$

3.5.2 H1: Data Assumptions

Prior to conducting the OLR, the data assumptions that precede OLR must be satisfied. OLR has four assumptions, which are: i) Dependent variable is ordered, ii) One or more of the independent variables are either continuous, categorical or ordinal, iii) no multi-collinearity and iv) proportional odds. The first two assumptions are tested based on inspection of the response and the factors, respectively. The absence of multicollinearity was determined by conducting a linear regression to calculate the Variance Inflation Factor (VIF) for each factor. If one or more VIF was greater than 5, the largest value was removed and the regression was repeated. This process continued until all VIFs were less than 5.

The assumption of proportional odds was assessed by modeling the data in a series of binary logistic regression models that segmented the response variable (Project Rating) at each cumulative level (O'Connell, 2006). The factor coefficients were then used to calculate the logit at each factor level for the binary logistic regression and these lines were plotted. If the assumption of proportional odds is maintained, the lines will be parallel. If the proportional odds assumption is not satisfied, the factors that violate the assumption may still be considered in the OLR model development. However, the final model would now be considered partial proportional odds (Sasidharan, 2014) and the regression equation would need to include coefficients at each factor level rather than a single coefficient for each factor.

3.5.3 H1: Data Preparation

For developing the OLR model, Minitab ("Minitab, LLC ", 2018) was used. To conduct the analysis, all data needed to exist in numeric format. All factors, including continuous and ordinal text, were recoded to fit within ordinal categories using Microsoft Excel. For continuous factors, custom binning was conducted based on the context of the innovation indicator. For text-based factors, each entry was converted to the proper level within the ordinal scale. Table 3-8 provides an example of the raw data for select innovation indicators and Table 3-9 provides the same data converted to ordinal levels. These ordinal values correspond to the same levels that were defined in the factor tables included above.

Table 3-8. Example raw data for select innovation indicators.

Project	Fiscal Year	PI IRAD Experience	PI Years of Experience	PI Level	PI Degree	Team Unique Majors	Success Rating
1	2018	1	34	Senior II	PhD	3	2
2	2018	3	9	Senior I	PhD	4	2
3	2018	5	20	Principal	PhD	5	4
4	2018	1	6	Senior I	Master's	4	5
5	2018	1	10	Senior I	PhD	3	3
6	2018	0	9	Senior I	PhD	5	5
7	2018	0	21	Senior II	PhD	10	4
8	2018	0	13	Senior I	PhD	3	2
9	2018	1	9	Senior II	PhD	6	3
10	2018	4	34	Principal	PhD	2	3
11	2018	2	16	Senior II	Master's	2	4
12	2018	1	9	Senior II	PhD	4	5
13	2018	3	10	Senior II	PhD	4	2
14	2018	4	28	Principal	PhD	3	3
15	2018	2	9	Senior II	PhD	4	4

Table 3-9. Example converted data for select innovation indicators.

Project	Fiscal Year	PI IRAD Experience	PI Years of Experience	PI Level	PI Degree	Team Unique Majors	Success Rating
1	1	2	4	4	3	2	2
2	1	2	2	3	3	3	2
3	1	3	3	5	3	3	4
4	1	2	2	3	2	3	5
5	1	2	2	3	3	2	3
6	1	1	2	3	3	3	5
7	1	1	4	4	3	3	4
8	1	1	3	3	3	2	2
9	1	2	2	4	3	3	3
10	1	3	4	5	3	2	3
11	1	2	3	4	2	2	4
12	1	2	2	4	3	3	5
13	1	2	2	4	3	3	2
14	1	3	4	5	3	2	3
15	1	2	2	4	3	3	4

3.5.4 H1: Model Training

The model training was performed with 70% of the project data. These data were selected randomly using MS Excel and evaluated for maintaining a distribution representative of the full dataset. Multiple OLR model construction methods were used. First, step-wise, forward selection was used to build up a model one factor at a time. With each model iteration, Minitab produced a model result that included the regression model and associated analysis (response information, logistic regression table, test of all slopes equal to zero, goodness-of-fit test, and measures of association). Additionally, the coefficients of the estimation equation and the event probabilities were also provided. Each model iteration was examined using various factors to assess model fitness, including the goodness-of-fit and measures of association criteria while maximizing the number of included factors. The second model development method employed step-wise, backward elimination. The initial OLR model included all factors. The factors were examined for significance. The factor with the greatest p-value was removed from future model development and OLR was performed with the remaining factors until all factors were significant. These model refinement iterations were used to choose a model that was significant, met the goodness-of-fit and measures of association criteria while minimizing the number of included factors.

3.5.5 H1: Model Testing

The regression model developed with the training data was used to test the ability of the model to correctly predict the likelihood of project success. Using the intercept and the coefficients from the OLR conducted on the training data, predictions of the

probability of project success were calculated for the remaining 30% of the data. Minitab was used to generate a predicted probability (P_{pred}) for each level (j) of success.

$$P_{pred}\ (Y\ \leq\ j \mid x_1, x_2, \ldots x_p)\ =\ \frac{e^{\alpha+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}}{1+e^{\alpha+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p}} \quad (3.4)$$

The individual predicted probabilities (P_{pred}) were then calculated by subtracting all values that have occurred at a lower ordinal level from the ordinal level of interest.

$$P_{pred}(Y = j \mid x_1, x_2, \ldots x_p) = P(Y \leq j \mid x_1, x_2, \ldots x_p) - P(Y \leq j - 1 \mid x_1, x_2, \ldots x_p) \quad (3.5)$$

Once the predicted Project Rating probabilities were calculated, the level with the maximum predicted probability was chosen as the new Project Rating for each test. Models are often deemed valid when they can accurately classify the response for 70% of their dataset (Jones, 2009). However, this performance accuracy is often targeted for models classifying between binary responses, where chance is 50%. The OLR model being developed here has five potential outcomes. Moreover, exact match classification accuracy alone is not sufficient in describing general model reliability and prediction capability (Lu, Wang, & Tolliver, 2019). Therefore, additional parameters should be assessed to find the best performing model.

A total of seven criteria were included to compare various candidate models and to inform selection of the final model (Lu et al., 2019). The prediction error ($e_{(i)}$), also known as a residual, is a measure of the discrepancy between the observed response and the predicted response (3.6). This error was used as the basis for calculating two measures of prediction error: sum of absolute residuals (SAR) (3.7) and sum of residual sum of squares (RSS) (3.8). Bias, which indicates how much a model overpredicts or underpredicts a response, was calculated. Additionally, a calculation was made for

Accuracy (3.10), which also indicates the difference between predicted and observed responses. Lastly, the percentage of exact predictions, predictions within 1 level (Lu et al., 2019) and correct predictions of an IRAD project with the potential to transition (Project Rating = 3+) were calculated and used for model comparison.

$$\text{error}_{(i)} = y_i - \hat{y}_{(i)} \tag{3.6}$$

$$\text{Sum of Abs Residuals} = \sum_{i=1}^{n} |e_{(i)}| \tag{3.7}$$

$$\text{Residual of Sum Squares} = \sum_{i=1}^{n} e^2{}_{(i)} \tag{3.8}$$

$$\text{Bias} = 10^{1/n} \sum_{i=1}^{n} log_{10}(\frac{\hat{y}_i}{y_i}) \tag{3.9}$$

$$\text{Accuracy} = 10^{1/n} \sum_{i=1}^{n} |log_{10}(\frac{\hat{y}_i}{y_i})| \tag{3.10}$$

Candidate models were evaluated against one another based on the values calculated for all seven of these parameters. The best model developed using forward selection and rearward rejection will be compared to determine which model will be selected for implementation.

3.6 H2: Model Validation and Implementation Methods

H2: Implementing changes identified by the decision support tool (DST) will improve all project success ratings to 3 or more.

The trained and tested model is implemented in a decision support tool (DST). The DST allows the PM to enter IP factors for a given project. The software then calculates the probability of achieving each potential Project Rating and chooses the maximum probability as the Project Rating. The DST allows the PM to modify IP factors

and determine the impact of the changes on Project Rating. Additionally, the tool will provide suggestions regarding what practical steps could be taken to achieve the new IP factor level. Based on the feasibility of each potential action, the PM can then make a decision to actually implement the change to the innovation process for their entire portfolio or just a single project. This section will describe the DST and provide the methods used to validate the model.

3.6.1 H2: Decision Support Tool Design

The DST provides the PM the ability to simulate a new project, or explore changes to the IP of an existing project, and determine the impact of that change on the probability of project success. The DST will provide options, such as suggesting IP modifications, to improve project success while controlling for cost. The PM will also have the opportunity to explore manual changes to the IP to determine other IP designs, such as revised proposal review and selection methods or increased cost, capable of improving the likelihood of project success. The DST interface (MS Excel) is shown in Figure 3-2. This homepage allows the user to assess the probability of project success, learn more about the supporting information associated with the IP factors as well as the methods used to generate the statistical model. Figure 3-3 is the interface where the PM will input known or desired project factor levels. The IP factors are entered, via dropdown menu, on the left side of the interface. The Project Rating probabilities are then calculated as shown on the bottom right of the page. To iterate on IP design, factor modifications can be made in real time to determine their effect on project success probability.

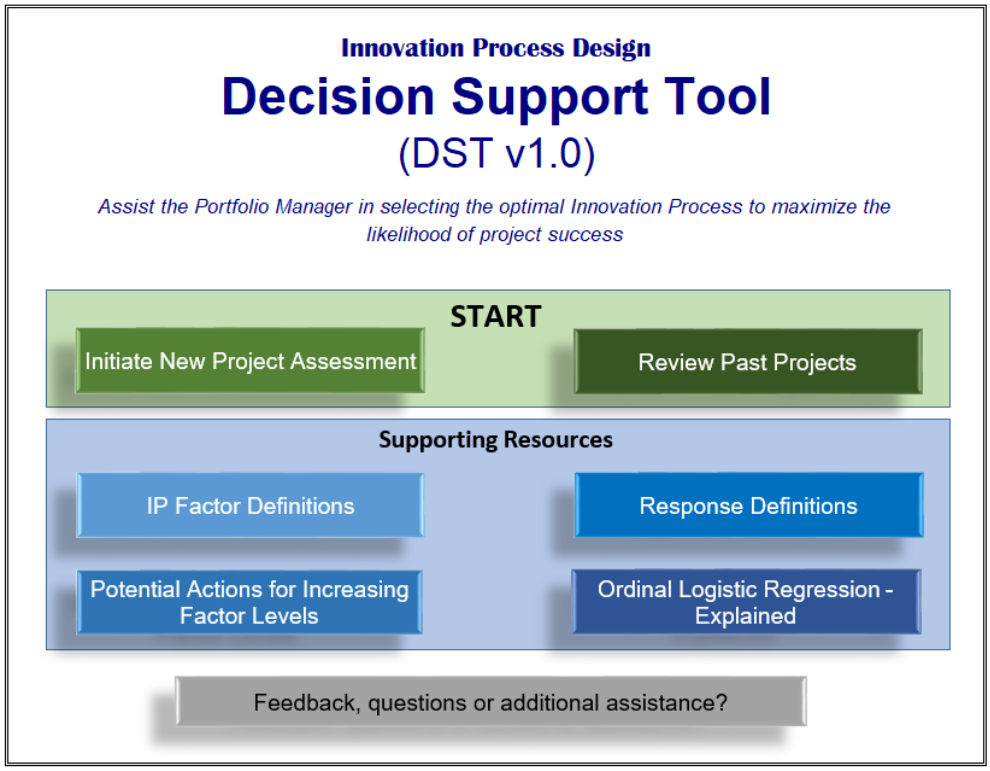


Figure 3-2. The Initial interface for the Innovation Process Design Decision Support Tool.

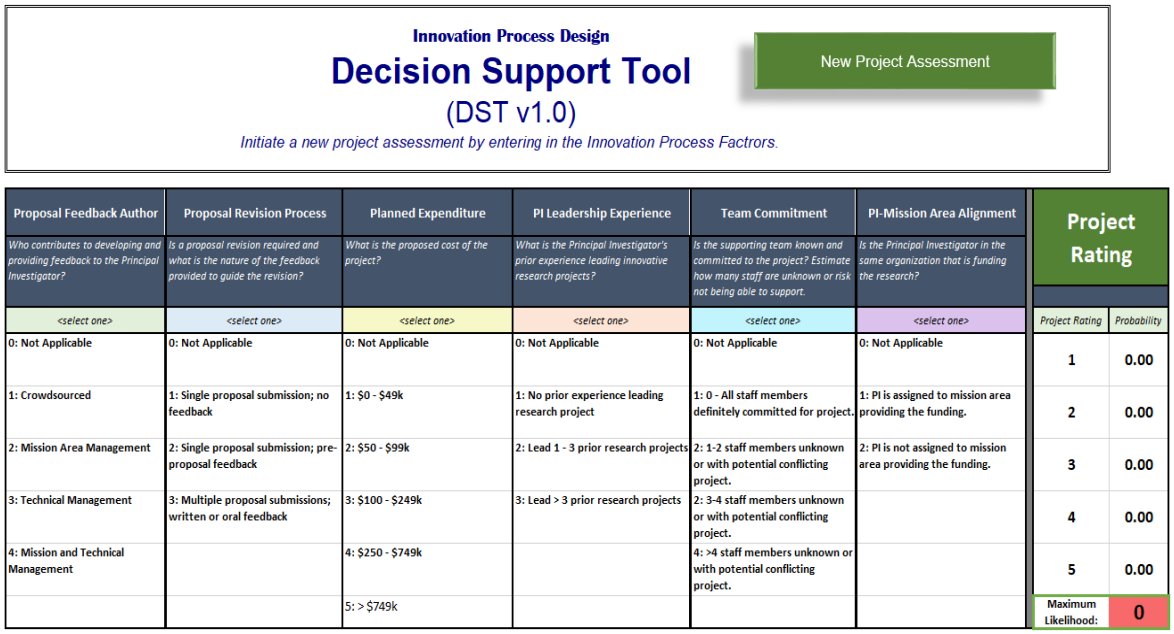


Figure 3-3. Project assessment interface page within the Innovation Process Design Decision Support Tool.

3.6.2 H2: Model Validation

Forty projects were selected as a simulated portfolio to validate the ability of the DST to assist a PM in making IP factor changes that result in improved values of Project Rating. The forty projects were randomly selected from those projects that had a Project Rating less than or equal to 4 (because a Project Rating of 5 cannot be improved) and were an exact match between the model prediction and the assessed Project Rating. The DST was then used in a series of project modification strategies developed from the perspective of the PM. The strategies were evaluated to determine if specified factor changes would significantly impact the Project Rating for the portfolio. Two different strategies were employed:

i) Single Factor Modification: The PM chooses a single factor to be modified for all projects in the portfolio, while all other factors are held constant. For example, the PM institutes a process where all proposal feedback must include technical and mission management (i.e., Feedback Author = 4).

ii) Multiple Factor Modification: The PM chooses multiple factors to modify simultaneously for the entire portfolio of projects while all other factors are held constant. For example, the PM could require that all projects be less than $100k and must have PIs with 20 years of experience.

To evaluate H2, the impact of these factor changes on Project Ratings must be determined. The new Project Rating probabilities are calculated by the DST using the modified factor levels and the OLR model coefficients (Eqn. 3.4 and Eqn. 3.5). The Project Rating level with the maximum probability was selected as the modified Project

Rating for each project. Once this process was complete, a non-parametric test was used to determine if the median of the two populations (original portfolio vs modified portfolio) was statistically different. The Wilcoxon Signed Rank Test for Matched Pairs was chosen to provide this evaluation (MiniTab). This test assesses if there is a statistically significant difference between the median of two related groups. Specifically, the Project Ratings for the portfolio before and after any factor changes are compared. This test has a null hypothesis (H_0) that assumes the median of the two populations (x, y) are equal:

$$H_o\colon \eta_x - \eta_y = 0 \tag{3.11}$$

If the p-value associated with this test is ≤ 0.05, then the populations are presumed different. This is an indicator that the IP factor modifications resulted in an improvement to the probability of project success. In practice, the PM would then investigate projects that are predicted to remain below a rating of 3 post-modification to determine what modifications, if any, would elevate the Project Rating to 3 or greater.

Chapter 4—Results

4.1 Introduction

This chapter provides the results from the analysis of an Independent Research and Development (IRAD) project database for the purpose of training and testing a statistical model that describes the relationship between Innovation Process (IP) factors and the likelihood of project success. The statistical model is then validated and implemented as the basis for an IP Decision Support Tool (DST).

Section 4.2 describes the initial dataset and the use of exclusion and inclusion criteria to determine the final dataset. The distribution of the factors and response levels for the refined dataset is also described.

Section 4.3 provides the results from the training of the Ordinal Logistic Regression (OLR) model and evaluates the two best models for comparison. Both models were then evaluated during model testing and a final model was selected for validation and implementation.

Section 4.4 describes the validation of the OLR and implementation into a DST. The results are used to determine which combination of factors could be changed to satisfy all projects having the potential for future research investment (Project Rating = 3+). The implementation of this model into a DST is described.

4.2 Project Dataset Creation

4.2.1. Initial Project Dataset Refinement

The initial query of the APL IRAD Management System (IMS) between the years of 2016 to 2019 returned 1279 projects worth a total investment of $210M. Using the unique IRAD project identifier code (PIC), the projects were cross-referenced with the

APL staffing and labor tracking databases to gather the data for each factor from the three phases of the IP.

The 1279 projects were overseen by twelve APL business units and a cross-enterprise innovation initiative, termed Project Catalyst. To refine the database based on criteria outlined in Chapter 3 (Table 3-5), four inclusion criteria were applied to the initial dataset at the organization level. Upon applying the inclusion criteria to the initial dataset, 53% of the projects (676) satisfied all criteria and remained in the dataset. These projects were distributed across five business units and Project Catalyst. The projects from the other seven business units were eliminated since these organizations did not meet at least one of the inclusion criteria.

The reduced dataset was then evaluated at the project level. Exclusion criteria (Table 3-6) were applied to determine project data completeness, quality assurance and interpretability. Based on these criteria, an additional 197 projects were removed from the dataset, resulting in a final dataset of 479 projects totaling $83M in investment (Figure 4-1). No project types were fully excluded based on the project-level exclusion criteria.

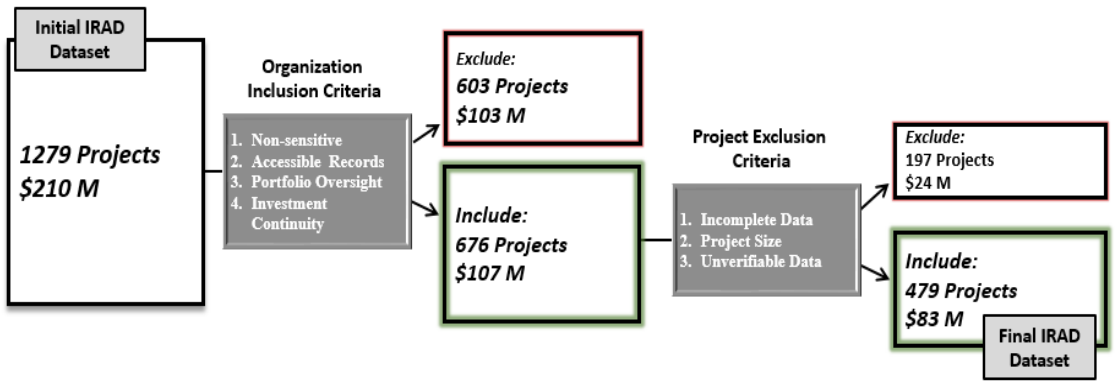


Figure 4-1. Dataset filtering steps resulting in final project dataset.

The final dataset includes projects from 2016-2019 with the distribution included in Table 4-1. Approximately 66% of the projects occurred in the last two years of the period of interest due to the stringent data quality inclusion criteria and an increase in IRAD resource allocation during those years. The average project investment was consistent over the four years, with three of the four years nearly $175k per project. The distribution of the Innovation Process (IP) factors will be discussed in more detail below.

Table 4-1. Final project dataset distribution by year and investment summary.

Project Year	Number of Projects	Total Investment ($k)	Average Investment per Project ($k)
2016	68	10,279	151
2017	95	16,701	175
2018	143	25,384	177
2019	173	30,214	174
Total	**479**	**82,580**	**172**

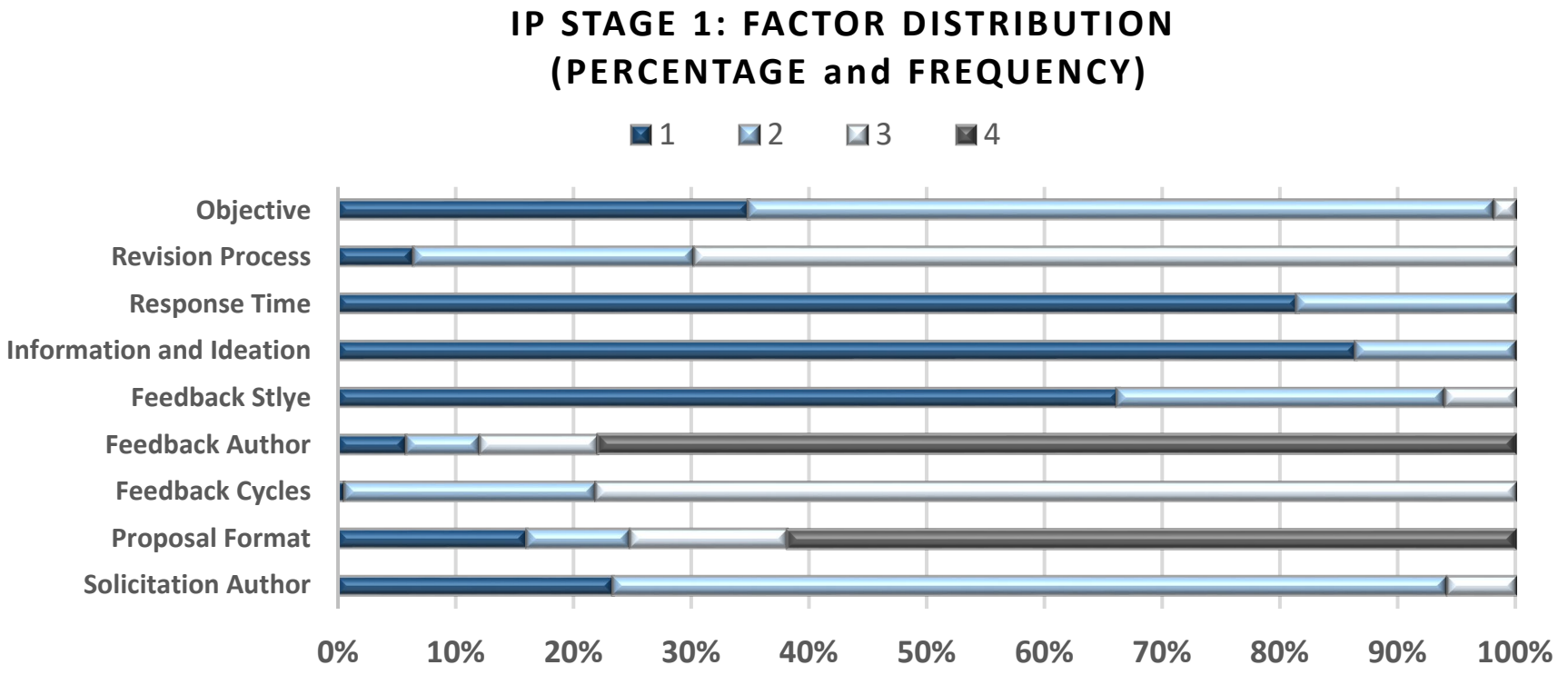
4.2.2 Dataset Distribution: Factors

A total of thirty-six IP factors were identified, collected and analyzed to determine a potential correlation to project outcomes. As provided in Chapter 3, nine factors were defined for Stage 1 of the IP, seven factors for Stage 2, eighteen factors for Stage 3. Two additional factors, the year in which the project was funded and the organization that funded it, were included in the statistical analysis to determine if these factors influenced project success. All collected data for each of these factors was converted to ordinal scales as defined in Chapter 3.

Solicit is the first stage of the APL IRAD IP. This stage initiates the overall IRAD process when each organization composes and publishes a solicitation for proposals. The proposal solicitation signals the organization's investment priorities, describes all aspects of the proposal submission process and includes additional details, such as how a Principal Investigator (PI) may gain assistance with proposal development. Figure 4-2 provides the results for each factor's distribution across the defined ordinal scales. For example, nearly 37% (176) of the 479 projects have an objective of non-mission oriented research (NMOR) rather than mission oriented research (MOR). Therefore, the OLR will permit an assessment of the impact of a tech push approach (NMOR) versus tech pull approach (MOR) on project success. Similarly, all organizations allowed for some level of feedback and revised proposals. This analysis will determine if the feedback style (written, verbal or crowdsourced) and by whom it was delivered (mission management, technical management, crowdsourced or some combination therein) are statistically significant factors in determining project success.

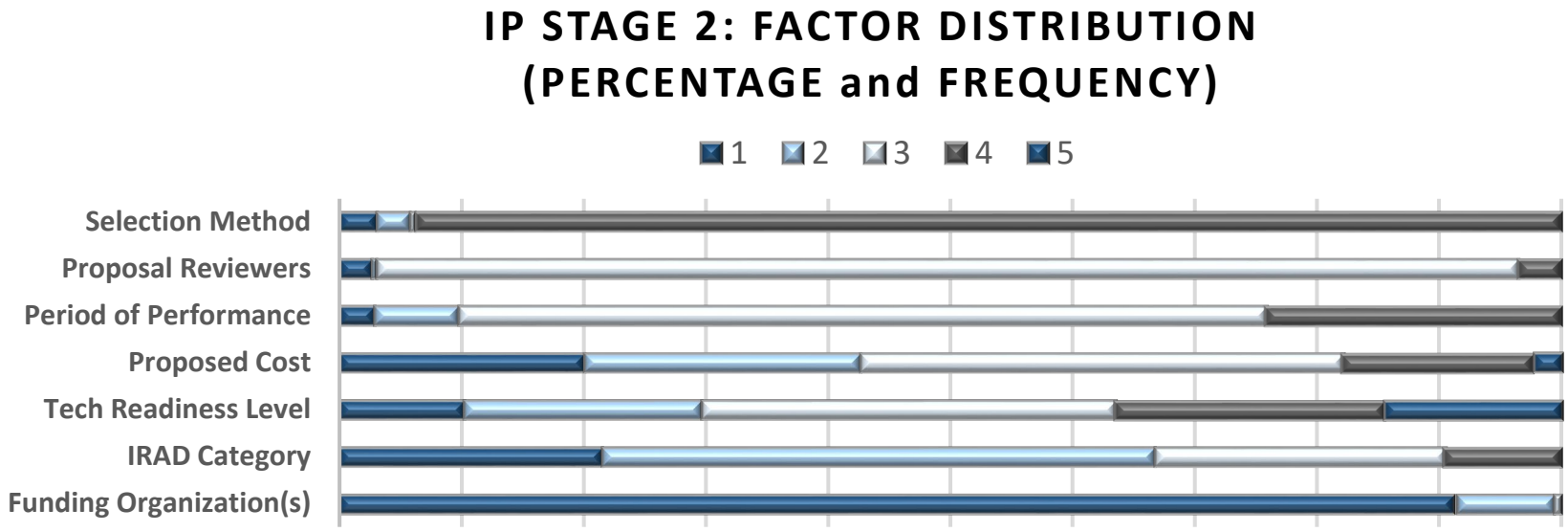
Select is the second stage of the APL IRAD IP. The selection process includes factors that define the evaluation of the submitted proposals and the decision to resource them. The distribution of these factors are included in Figure 4-3. Some factors were largely weighted toward a single level. For example, nearly all proposals (93%) were selected by a combination of technical and mission management. The proposed cost of the proposals was more evenly distributed with levels 1 – 5 occurring at proportions of 20%, 23%, 39%, 16% and 2%, respectively. Similarly, the IRAD categories were 22% Basic Research, 45% Applied Research, 24% Development and 9% Systems and Other

Concept Formulation Studies. The OLR will determine if the IRAD Category is significantly correlated to project success.



	Solicitation Author	Proposal Format	Feedback Cycles	Feedback Author	Feedback Stlye	Information and Ideation	Response Time	Revision Process	Objective
1	112	77	3	28	317	414	390	31	167
2	339	42	102	30	133	65	89	114	303
3	28	64	374	48	29	0	0	334	9
4	0	296	0	373	0	0	0	0	0

Figure 4-2. Stage 1 (Solicit) IP factor distribution (top – percentage; bottom – frequency) for all included projects (479).



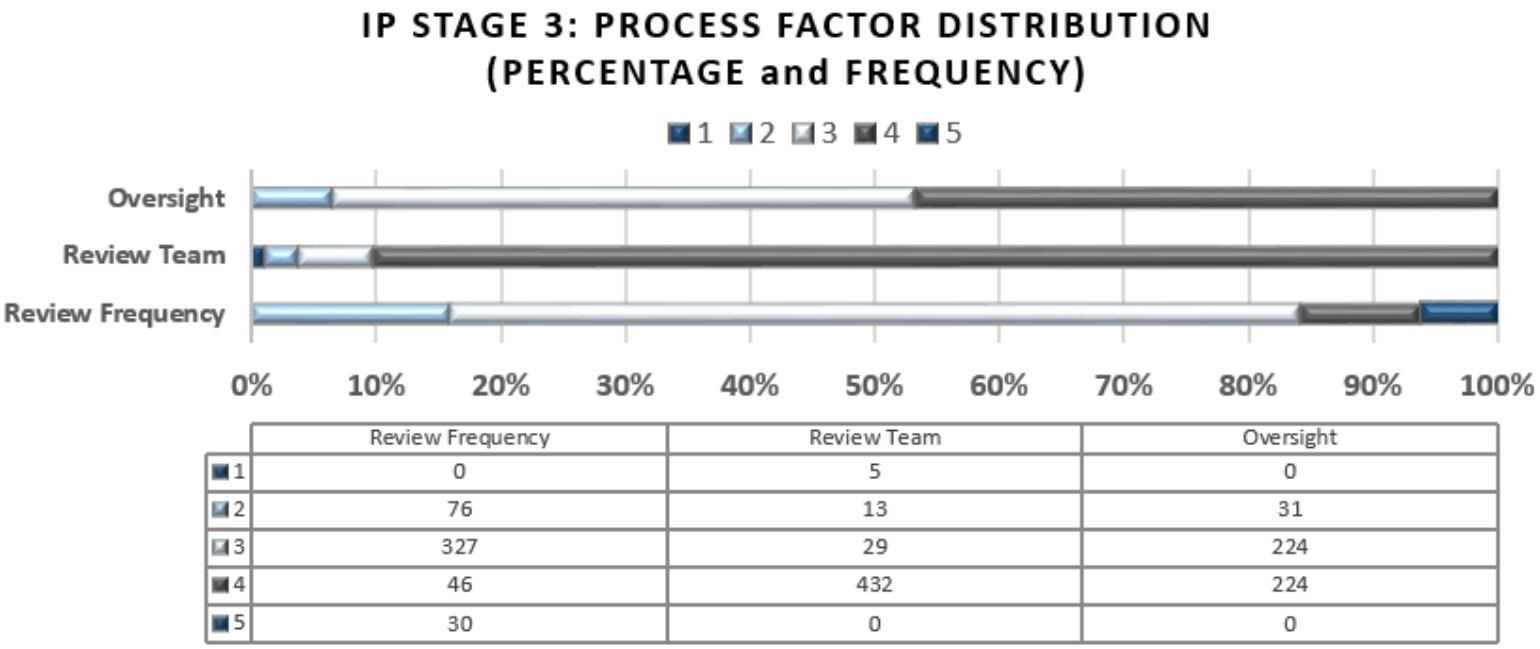
	Funding Organization(s)	IRAD Category	Tech Readiness Level	Proposed Cost	Period of Performance	Proposal Reviewers	Selection Method
1	436	103	49	96	14	13	15
2	39	216	93	108	33	2	13
3	3	114	162	189	316	447	2
4	0	46	106	75	116	17	449
5	0	0	69	11	0	0	0

Figure 4-3. Stage 2 (Select) IP factor distribution (top – percentage; bottom – frequency) for all included projects (479).

Manage is the third stage of the APL IP. This final stage includes all aspects of management oversight during project execution and is organized into process factors and project factors. Figure 4-4 provides the distributions for the three factors associated with the process of management. Analysis of these factors will determine if the manner in which project oversight and reviews occur is correlated to success. Figure 4-5 includes project-specific factors that may correlate to project success. For example, 59% (293) of the projects had an IRAD PI conducting their first IRAD project (referencing project records beginning in 2015). Only 19% (92) of the projects were led by a PI who was not within the funding organization. In examining the potential significance of team composition on project success, 18% of the projects had no staff with a PhD degree while 40% of the projects had two or more PhDs on the team.

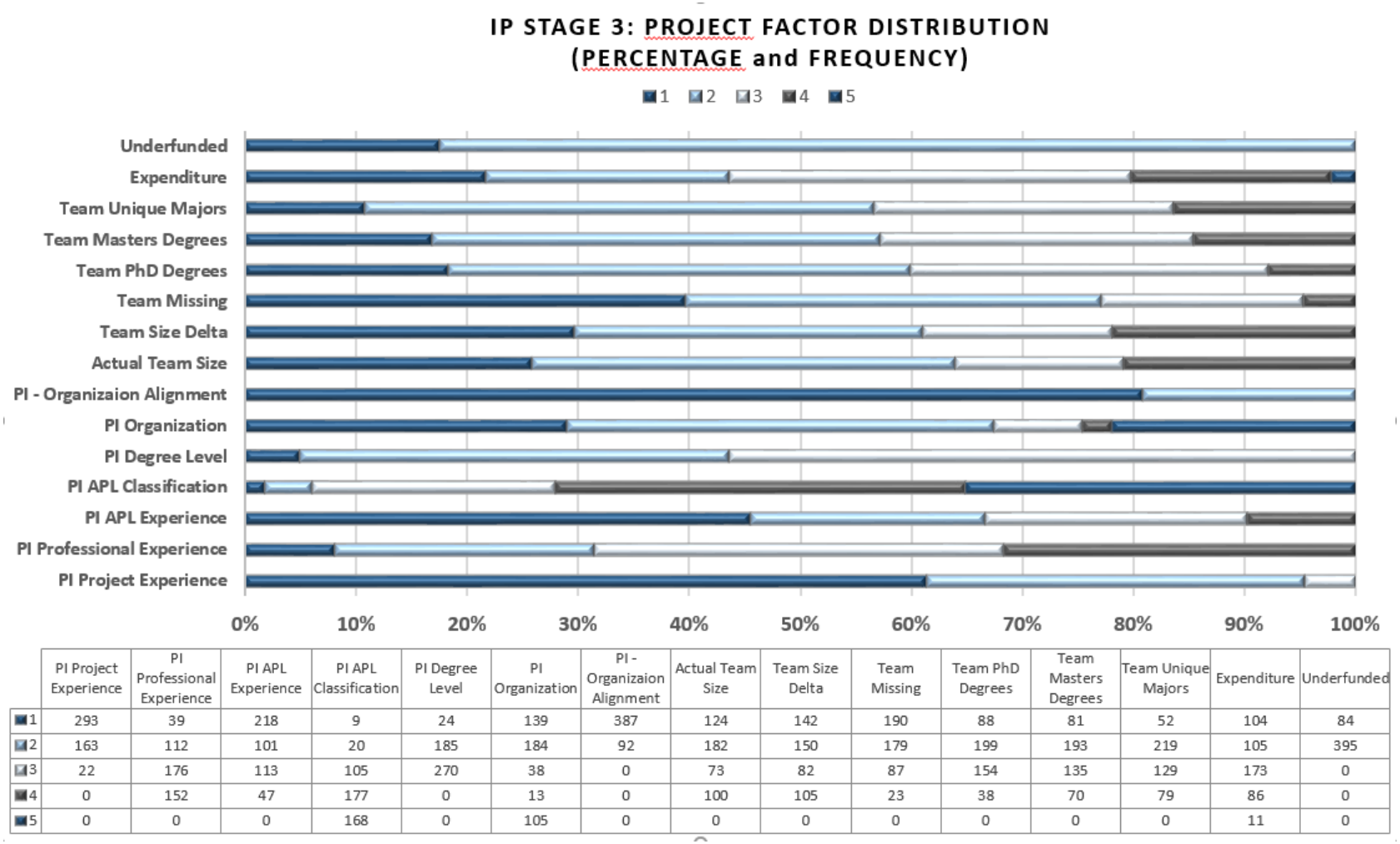
4.2.3 Dataset Distribution: Response

The scale for assessing Project Rating was defined based on each IRAD category and described in Table 3-7. The assessed ratings are provided in Table 4-2, separated by IRAD Category, and the distribution is summarized in Figure 4-6. Approximately 79% of the projects are rated as 3+ which means they have at least the potential opportunity to transition to future research or application at the conclusion of the project. However, 21% of the projects were either halted or did not make enough progress to warrant any further consideration for future investment or transition.



	Review Frequency	Review Team	Oversight
1	0	5	0
2	76	13	31
3	327	29	224
4	46	432	224
5	30	0	0

Figure 4-4. Stage 3 (Manage) IP process factor distribution (top – percentage; bottom – frequency) for all included projects (479).



	PI Project Experience	PI Professional Experience	PI APL Experience	PI APL Classification	PI Degree Level	PI Organization	PI - Organizaion Alignment	Actual Team Size	Team Size Delta	Team Missing	Team PhD Degrees	Team Masters Degrees	Team Unique Majors	Expenditure	Underfunded
1	293	39	218	9	24	139	387	124	142	190	88	81	52	104	84
2	163	112	101	20	185	184	92	182	150	179	199	193	219	105	395
3	22	176	113	105	270	38	0	73	82	87	154	135	129	173	0
4	0	152	47	177	0	13	0	100	105	23	38	70	79	86	0
5	0	0	0	168	0	105	0	0	0	0	0	0	0	11	0

Figure 4-5. Stage 3 (Manage) IP project factor distribution (top – percentage; bottom – frequency) for all included projects (479).

Table 4-2. Distribution of the Project Rating response variable by IRAD Category.

Project Rating \ IRAD Category	1	2	3	4	Total
1	5	9	8	1	**23**
2	20	30	13	13	**76**
3	28	82	32	17	**159**
4	34	69	41	11	**155**
5	16	26	20	4	**66**

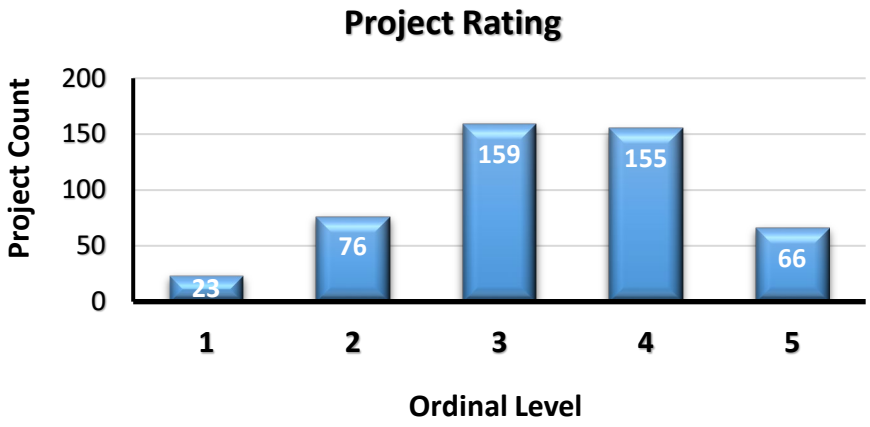


Figure 4-6. Distribution of Project Rating scores for all included projects (479).

4.3 H1: Regression Model Development and Selection

H1: Five factors impact the likelihood of project success: Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Funding Level

4.3.1 H1: Model Training Data Preparation

OLR was used to develop a statistical model to evaluate H1, which considers the impact of the IP factors on the likelihood of the response, Project Rating. To create the

dataset for model training, 70 percent of the projects were randomly selected from the total dataset (479 projects). These 334 projects became the training dataset. To evaluate how well the randomization maintained the distribution of the factor levels, Figure 4-7 shows the number of occurrences for each factor at every level in the training dataset divided by the total occurrences in the entire dataset, termed the Training Data Frequency Ratio. This calculated ratio fell between 0.60 and 0.80 for nearly all (92%) of the training dataset factors. The exceptions occurred when there were very few data points within the dataset for a specific factor level. Similarly, the distribution of Project Rating for the training dataset was plotted against the full dataset in Figure 4-8. The similar profile between the training data and then full dataset indicates that the distribution of responses across the ordinal scale in the full dataset was preserved in the creation of the training dataset.

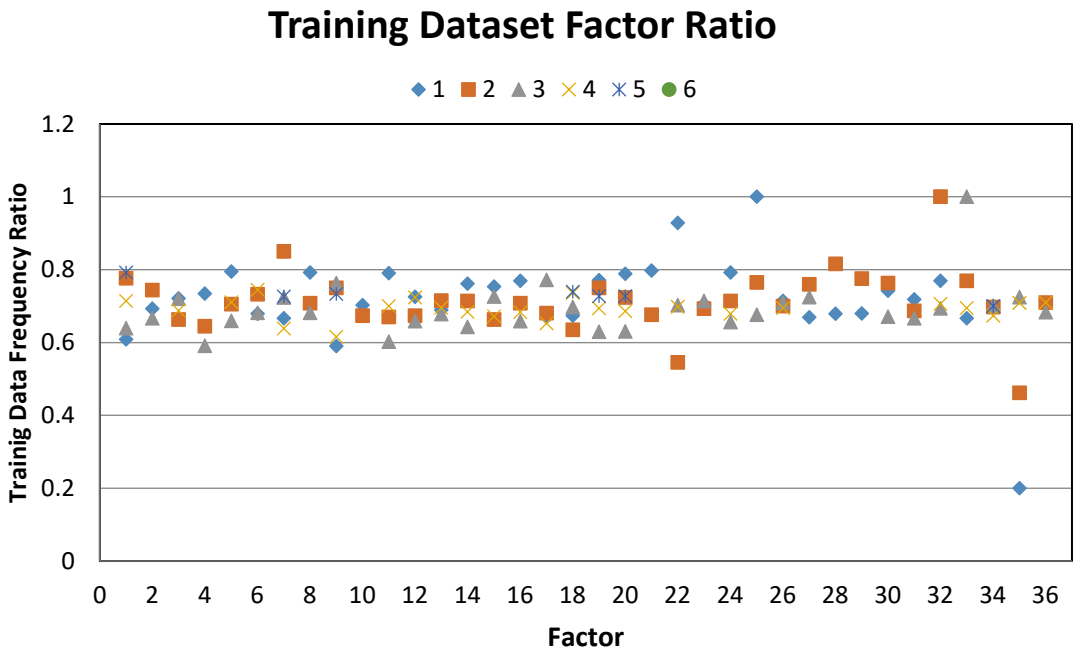


Figure 4-7. Training dataset factor distribution compared to whole dataset.

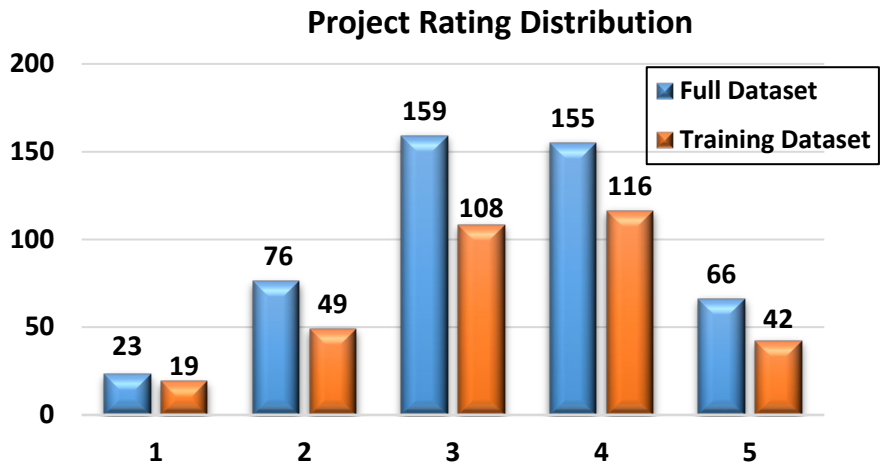


Figure 4-8. Project Rating distribution for the full and training dataset.

Prior to conducting OLR, four assumptions regarding the data must be satisfied. Table 4-3 provides the assumptions along with the evaluation method, evaluation outcome and confirmation that the assumptions were satisfied. The first two assumptions are met simply based on inspection of the dataset. Specifically, the response (Project Rating) is an ordered variable and all factors are ordinal, which satisfies the first and second assumptions, respectively. To evaluate the third assumption, which seeks to identify multicollinearity by determining the Variance Inflation Factor (VIF) for each factor, the sequential elimination process described in Chapter 3 was conducted. Five factors were sequentially eliminated for VIF > 5 and no longer considered in the modeling effort. A sixth factor, Team Size, which had a marginal VIF of 5.90, was initially included in model construction. However, it was not found to be significant and it did not contribute to an improved model. Therefore, Team Size was removed from further model development. The initial VIF from the first assessment and final VIF from

the final assessment are provided in Table 4-4. The Minitab output is provided in the Appendix (Figure A-1 and Figure A-2).

Table 4-3. Ordinal Logistic Regression data assumptions, evaluation method and outcome.

Assumption	Evaluation Time / Method	Outcome	Assumption Satisfied?
Ordered response variable	Pre-OLR: Evaluate dependent variable to confirm ordered response.	The response variable (Project Rating) is ordered with 5 levels, as defined in Chapter 3.	Yes
One or more factor is continuous, categorical or ordinal	Pre-OLR: Evaluate if factors are continuous, categorical or ordinal.	All factors are continuous, categorical or ordinal, as defined in Chapter 3.	Yes
No Multicollinearity	Pre-OLR: Evaluate the VIF for all factors; sequentially remove any factor with VIF > 5	Six factors were removed for VIF > 5: • Funding Org. • Team Size • Proposal Format • Feedback Cycles • Selection Method	Yes
Proportional Odds	Pre-OLR: Conduct test to assess equal slopes for factor levels.	Proportional odds maintained (parallel lines) for 25 of 30 factors.	Yes

Table 4-4. Variance Inflation Factor results.

Factor	Initial VIF	Final VIF
Funding Organization	22.76	Removed
Partnering Funding Organizations	1.45	1.41
Fiscal Year	1.76	1.46
PI IRAD Experience	1.36	1.34
PI Professional Experience	2.96	2.96
PI APL Experience	1.98	1.95
PI Classification	3.91	3.84
PI Degree Level	1.76	1.74
PI - Organization	4.80	3.94
PI – Organization Alignment	2.30	1.99
Team Size	5.90	Removed
Team Size Delta	3.42	2.66
Team Missing	1.41	1.36
Team Doctoral Degrees	2.82	2.49
Team Master's Degrees	3.57	2.89
Team Unique Major	2.44	2.29
IRAD Category	1.48	1.45
Tech Readiness Level	1.50	1.48
Expenditures	3.03	2.79
Underfunded	1.17	1.16
Period of Performance	2.25	2.24
Solicitation Author	9.55	2.25
Proposal Format	23.03	Removed
Feedback Cycles	20.29	Removed
Feedback Author	11.10	3.34
Feedback Style	17.24	4.31
Information and Ideation	4.87	3.25
Response Time	8.30	3.96
Revision Process	7.31	3.00
Objective	3.38	2.93
Proposal Reviewers	2.78	1.11
Selection Method	45.50	Removed
Review Frequency	4.90	4.64
Review Team	1.49	1.47
Oversight	4.08	3.70

The fourth assumption of proportional odds asserts that each factor has a uniform effect at each cumulative split of the response (Project Rating). The 30 remaining factors were evaluated with a series of four binary logistic regression models, one model for each cumulative split of the response variable. Twenty-five factors demonstrated uniform impact on the logit response for each factor level by having parallel lines when plotted for each cumulative split, which satisfies the proportional odds assumption. Figure 4-9 provides the results for Team Size Delta to demonstrate this evaluation. Five factors did not demonstrate parallel lines and therefore do not satisfy the proportional odds assumption: Response Time, Information Session, Proposal Reviewers, Oversight, and Team Masters Degrees. Figure 4-10 provides the results for Team Masters Degrees as an example for which the proportional odds assumption is not satisfied. For those factors that did not satisfy the proportional odds assumption, they will not be removed from model development. Rather, if they are found to be significant factors in model training, then a partial proportional odds approach will be employed where coefficients specific to each response level will be used to calculate model predictions in the final OLR.

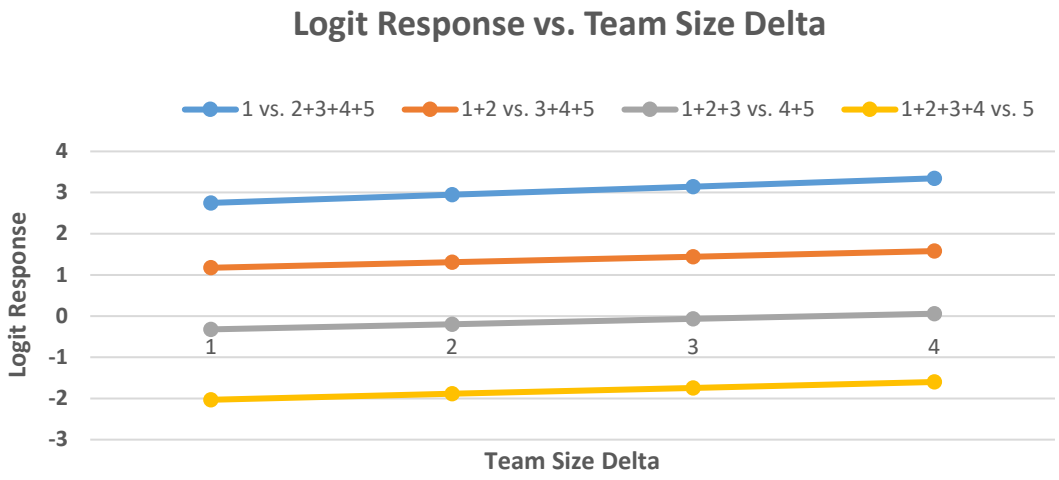


Figure 4-9. Proportional odds evaluation satisfied for Team Size Delta.

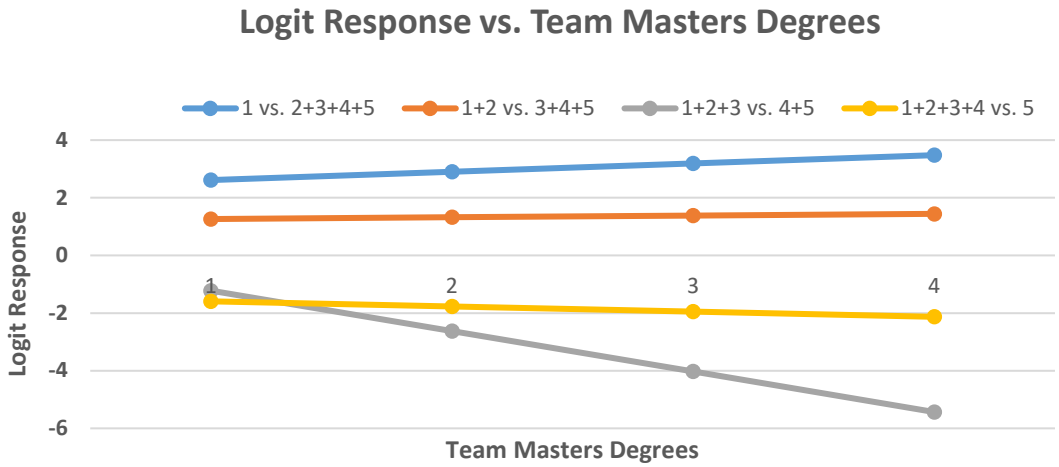


Figure 4-10. Proportional odds evaluation rejected for Team Masters Degrees.

4.3.2 H1: Model Training Results

To determine the best OLR model relating IP factors to Project Rating, step-wise forward and step-wise backward model development methods were manually performed with the training data. More than a hundred candidate models were created and the most

promising had their fitness was evaluated using the parameters described in Chapter 3. At the conclusion of this process, the two best models, one each from the forward and backward methods, were selected for model testing. The IP factors identified for best explaining the training data are provided in (Table 4-5). Model 1, using backward elimination, is potentially the most parsimonious model, as it has the least amount of factors (4) with the greatest goodness of fit (Pearson = 0.978). For the training data, Model 1 had an exact match accuracy of 34.1% and matched 85.6% of the Project Ratings within one level. Model 2 was the result of the forward selection process, which maximized the number of factors (6) while targeting a modest goodness of fit (Pearson = 0.656). This model had an exact match accuracy of 44.3% and matched 88.3% of the Project Ratings within one level, both of which are scores that were better than Model 1.

Model 2 included all of the factors hypothesized in H1 to have significance (Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Expenditure), along with an additional factor, PI-Org. Alignment. Although Expenditure was slightly above the specified significance threshold, the inclusion of this factor in Model 2 was found to improve training and testing performance. Model 1 only included three of the factors from H1 (Proposal Revision Process, Principal Investigator Experience, and Expenditure) while also including PI-Org. Alignment. The Minitab OLR outputs, including significance levels and coefficients, are provided in the Appendix (Figure A-3 and Figure A-4). The next step was to evaluate the performance of both models using the test data.

Table 4-5. Final OLR models based on training dataset.

Assessment Criteria	**Model 1** (Backward Elimination)	**Model 2** (Forward Selection)
Significant Factors (p<0.05)	PI IRAD Experience PI-Org. Alignment Expenditures Revision Process	PI IRAD Experience (PIE) PI-Org. Alignment (POA) Team Missing (TM) Expenditure (Exp) Feedback Author (FA) Revision Process (RP)
Log-Likelihood	-465.890	-449.273
Goodness of Fit	Pearson = 0.978 Deviance = 0.946	Pearson = 0.656 Deviance = 0.998
Measures of Association	Concordant % – 59.5 Discordant % – 35.3 Somers 'D - 0.24 Krusk.Gamma- 0.26	Concordant % – 66.7 Discordant % – 31.5 Somers 'D - 0.35 Krusk.Gamma- 0.36
Training Accuracy - Exact Match (%)	34.1	44.3
Training Accuracy – Within 1 Difference (%)	85.6	88.3

4.3.3 H1: Model Testing Results

The predictive performance of Model 1 and Model 2 were tested using the remaining 30% of the original dataset. Model 1 coefficients generated from the backward elimination OLR (Figure A-3) were used to predict Project Rating. The equations for Model 1 calculations are as follows:

$$\mathrm{P}_{\text{pred M1}}\,(\mathrm{Y}=1) = \frac{e^{-4.13772-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}}{1+e^{-4.13772-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}} \tag{4.1}$$

$$\mathrm{P}_{\text{pred M1}}\,(\mathrm{Y}=2) = \frac{e^{-2.62481-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}}{1+e^{-2.62481-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}} - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=1) \tag{4.2}$$

$$\mathrm{P}_{\text{pred M1}}\,(\mathrm{Y}=3) = \frac{e^{-1.0631-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}}{1+e^{-1.0631-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}} - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=2) - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=1) \tag{4.3}$$

$$\mathrm{P}_{\text{pred M1}}\,(\mathrm{Y}=4) = \frac{e^{--0.849795-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}}{1+e^{-0.849795-0.254*[PIE]+1.144*[POA]-0.239*[Exp]+0*[RP=1]+0.517*[RP=2]+1.050*[RP=3]}} - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=3) - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=2) - \mathrm{P}_{\text{pred M1}}(Y=1) \tag{4.4}$$

$$\mathrm{P}_{\text{pred M1}}\,(\mathrm{Y}=5) = 1 - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=4) - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=3) - \mathrm{P}_{\text{pred M1}}(Y=2) - \mathrm{P}_{\text{pred M1}}(\mathrm{Y}=1) \tag{4.5}$$

Similarly, coefficients for Model 2 from the forward selection training data model (Figure A-4) were used in the OLR equations to calculate the predicted Project Rating. The equations determined for Model 2 are:

$$\mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=1) = \frac{e^{-4.01453-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*\ [Exp]-0.7546*[FA]+1.06}}{1+e^{-4.01453-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*[Exp]-0.7546*[FA]+1.063*[RP]}} \quad (4.6)$$

$$\mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=2) = \frac{e^{-2.41166-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*\ [Exp]-0.7546*[FA]+1.063*[RP]}}{1+e^{-2.41166-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*[Exp]-0.7546*[FA]+1.063*[RP]}} - \mathrm{P}_{\mathrm{pred\ M2}}(\mathrm{Y}=1) \quad (4.7)$$

$$\mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=3) = \frac{e^{-0.699088-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*\ [Exp]-0.7546*[FA]+1.06}}{1+e^{-0.699088-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*[Exp]-0.7546*[FA]+1.063*[RP]}} - \mathrm{P}_{\mathrm{pred\ M2}}(\mathrm{Y}=2) - \mathrm{P}_{\mathrm{pred\ M2}}(\mathrm{Y}=1) \quad (4.8)$$

$$\mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=4) = \frac{e^{1.30603-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*\ [Exp]-0.7546*[FA]+1.063}}{1+e^{1.30603-0.2683*[PIE]+0.8017*[POA]+0.3683*[TM]-0.1599*[Exp]-0.7546*[FA]+1.063*[RP]}} - \mathrm{P}_{\mathrm{pred\ M2}}(\mathrm{Y}=3) - \mathrm{P}_{\mathrm{pred\ M2}}(\mathrm{Y}=2) - \mathrm{P}_{\mathrm{pred\ M2}}(Y=1) \quad (4.9)$$

$$\mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=5) = 1 - \mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=4) - \mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=3) - \mathrm{P}_{\mathrm{pred\ M2}}(Y=2) - \mathrm{P}_{\mathrm{pred\ M2}}\ (\mathrm{Y}=1) \quad (4.10)$$

Model 1 and Model 2 equations were used to predict their respective Project Rating probabilities at each response level for all 145 projects in the test dataset. The maximum probability was then selected as the predicted Project Rating for each model. A sample of the results at each response level for 10 tests is provided in Table 4-6. Four of

the Model 1 predicted ratings match the actual rating whereas five of the Model 2 predicted ratings match exactly.

Table 4-6. Predicted Project Rating probabilities for ten projects from the testing dataset.

Project	Model 1 Prediction Proabilities					Model 2 Prediction Probabilities					PROJECT RATING Comparison		
	PR=1	PR=2	PR=3	PR=4	PR=5	PR=1	PR=2	PR=3	PR=4	PR=5	Model 1 Prediction	Model 2 Prediction	Actual
121	0.176	0.316	**0.330**	0.147	0.031	0.100	0.255	**0.398**	0.205	0.042	3	3	3
122	0.073	0.190	**0.367**	0.290	0.080	0.044	0.141	**0.372**	0.347	0.097	3	3	4
123	0.051	0.146	0.343	**0.348**	0.112	0.045	0.145	0.375	**0.341**	0.094	4	3	2
124	0.051	0.144	0.341	**0.350**	0.113	0.028	0.099	0.320	**0.410**	0.143	4	4	4
125	0.178	0.318	**0.329**	0.145	0.031	0.152	**0.319**	0.361	0.142	0.027	3	3	3
126	0.080	0.204	**0.370**	0.273	0.072	0.043	0.140	**0.371**	0.349	0.098	3	3	5
127	0.064	0.174	**0.361**	**0.311**	0.090	0.074	0.210	**0.403**	0.254	0.058	3	3	1
128	0.040	0.120	0.317	**0.384**	0.140	0.254	**0.375**	0.275	0.082	0.014	4	2	2
129	0.041	0.121	0.318	**0.382**	0.138	0.027	0.094	0.312	**0.417**	0.149	4	4	3
130	0.025	0.079	0.253	**0.432**	0.210	0.016	0.059	0.235	**0.459**	0.231	4	4	4

After completing the Model 1 and Model 2 calculations for Project Rating predictions, seven model performance criteria were used to assess which model might be best suited for implementation in the Decision Support Tool (DST). The results of the performance criteria calculations are provided in Table 4-7. Model 2 outperformed Model 1 in all seven criteria. Neither model achieved 70% of the exact match between predicted and known response, which is normally sought in a binary classifier. Model 1 achieved 37.2% and Model 2 achieved 40.7%. However, when the predictions were required to be within a single response level, then both models improved significantly with Model 2 achieving greater than 80%. The sum of residuals is less in Model 2 (112 vs. 135). Additionally, both Bias and Accuracy are lower in Model 2. Since Model 2 fared better in all seven performance criteria, Model 2 was selected as the final OLR model that best describes the impact of Innovation Process (IP) factors on Project Rating.

Model 2 satisfies H1. The five factors predicted to impact Project Rating were found to do so (Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Funding Level). Additionally, a sixth factor, the PI – Org. Alignment, was also found to be significant.

Table 4-7. Test data performance criteria.

Performance Criteria	**Model 1** (Backward Elimination)	**Model 2** (Forward Selection)
Exact Match	**37.2%**	**40.7%**
Within 1 Difference	**78.6%**	**82.1%**
Transition Prediction (3+)	**76.6%**	**77.9%**
Sum of Absolute Residuals	**125**	**112**
Sum of Residual Squares	**199**	**164**
Bias	**1.10**	**1.06**
Accuracy	**1.32**	**1.28**

4.4 H2: Model Validation and Implementation

H2: Implementing changes identified by the decision support tool (DST) will improve all project success ratings to 3 or more.

The trained and tested model was implemented within a decision support tool (DST). The DST allows the PM to enter IP factor levels for a given project and the tool will calculate the probabilities for each Project Rating. The PM can continue to use the tool to modify the IP factor levels to determine impact on predicted project success.

To address H2, two questions must be answered. First, will modifications to the IP factor level create a statistically significant improvement to the Project Rating? Second, will the Project Rating predictions improve sufficiently enough to raise all projects to a Project Rating of 3 or above? This section will answer these questions using the results from the model validation steps described in Chapter 3.

4.4.1 H2: Decision Support Tool

The DST provides the PM the ability to determine the Project Rating for a new project or explore the impact of IP factor modifications for an existing project. The DST project assessment interface was provided in Figure 3-3. The PM can input known or desired factor levels using drop down menus and then the project success probabilities are calculated. To illustrate this, below is an example from Project 207 in the training database. The original IP factor levels, calculated probabilities for each Project Rating level and the maximum likelihood Project Rating are shown in Figure 4-11. With a Project Rating equal to 2, this project would not successfully transition beyond the current investment. However, when changes are made to the IP factor levels, such as the Proposal Feedback Author now including technical and line management participation (=

4) and PI Leadership Experience being required for 3 or more prior projects (= 3), then the Project Rating increases to 4 (Figure 4-12). This improved rating indicates a high likelihood that the research project will transition beyond the current scope and receive future investment.

Proposal Feedback Author	Proposal Revision Process	Planned Expenditure	PI Leadership Experience	Team Commitment	PI-Mission Area Alignment
Who contributes to developing and providing feedback to the Principal Investigator?	*Is a proposal revision required and what is the nature of the feedback provided to guide the revision?*	*What is the proposed cost of the project?*	*What is the Principal Investigator's prior experience leading innovative research projects?*	*Is the supporting team known and committed to the project? Estimate how many staff are unknown or risk not being able to support.*	*Is the Principal Investigator in the same organization that is funding the research?*
2	*3*	*3*	*2*	*3*	*1*

Project Rating	
Project Rating	*Probability*
1	0.19
2	0.35
3	0.33
4	0.11
5	0.02
Maximum Likelihood:	2

Figure 4-11. Original IP factor levels used to calculate Project Rating.

Proposal Feedback Author	Proposal Revision Process	Planned Expenditure	PI Leadership Experience	Team Commitment	PI-Mission Area Alignment
Who contributes to developing and providing feedback to the Principal Investigator?	*Is a proposal revision required and what is the nature of the feedback provided to guide the revision?*	*What is the proposed cost of the project?*	*What is the Principal Investigator's prior experience leading innovative research projects?*	*Is the supporting team known and committed to the project? Estimate how many staff are unknown or risk not being able to support.*	*Is the Principal Investigator in the same organization that is funding the research?*
4	*3*	*3*	*3*	*3*	*1*

Project Rating	
Project Rating	*Probability*
1	0.04
2	0.13
3	0.36
4	0.37
5	0.11
Maximum Likelihood:	4

Figure 4-12. Modified IP factor levels used to calculate a new Project Rating.

4.4.2 H2: Model Validation Dataset

The OLR model validation was conducted with a set of forty projects randomly selected from those projects that were successfully classified during model development and had a Project Rating less than 5. Table 4-8 provides the details for each selected project in the validation dataset. For each project, Table 4-8 includes the IP factor levels, assessed Project Rating, and the predicted Project Rating with associated probabilities.

To evaluate H2, a series of validation assessments were performed with the DST. Two different sets of validation simulations were conducted: i) Single Factor Modification – a factor is modified to the same level for all projects while all other factors remain unchanged and ii) Multiple Factor Modification - multiple factors are modified simultaneously for all projects while the remaining factors are unchanged.

Table 4-8. Model validation dataset.

Project ID (Training Data)	Innovation Process Factor Levels						Model 2 Prediction Probabilities					Project Rating
	PI IRAD Experience	PI-MA Alignment	Team Missing	Expenditure	Feedback Author	Revision Process	PR=1	PR=2	PR=3	PR=4	PR=5	
3	1	1	2	2	4	3	0.053	0.163	0.388	0.315	0.081	3
17	2	2	2	1	1	1	0.089	0.237	0.402	0.224	0.048	3
34	1	1	1	4	2	3	0.112	0.273	0.391	0.186	0.037	3
36	2	1	2	1	4	3	0.047	0.151	0.380	0.333	0.090	3
41	3	2	2	5	3	2	0.041	0.135	0.366	0.356	0.102	3
60	1	1	2	1	4	3	0.061	0.183	0.397	0.288	0.070	3
140	2	1	2	4	2	3	0.122	0.287	0.384	0.173	0.034	3
149	1	1	1	4	2	3	0.112	0.273	0.391	0.186	0.037	3
206	2	2	2	1	1	1	0.113	0.274	0.391	0.185	0.037	3
207	2	1	3	3	2	3	0.191	0.349	0.327	0.113	0.020	2
208	1	1	2	1	2	3	0.227	0.366	0.296	0.094	0.016	2
218	1	2	1	4	3	2	0.044	0.141	0.372	0.347	0.097	3
229	1	1	3	4	4	2	0.020	0.071	0.265	0.448	0.196	4
232	1	1	1	2	4	3	0.037	0.123	0.354	0.373	0.113	4
236	2	1	2	4	2	3	0.122	0.287	0.384	0.173	0.034	3
239	1	1	2	2	2	3	0.200	0.354	0.319	0.107	0.019	2
240	3	1	1	3	4	3	0.014	0.053	0.219	0.462	0.251	4
241	2	1	1	4	4	3	0.021	0.075	0.274	0.444	0.187	4
244	1	1	1	1	4	3	0.043	0.140	0.371	0.349	0.098	3
246	2	1	1	4	3	2	0.015	0.057	0.229	0.461	0.238	4
247	2	1	2	1	4	3	0.047	0.151	0.380	0.333	0.090	3
248	1	1	3	3	2	3	0.236	0.369	0.289	0.090	0.016	2
262	2	1	1	2	4	3	0.028	0.099	0.320	0.410	0.143	4
265	1	1	1	1	4	3	0.043	0.140	0.371	0.349	0.098	3
267	2	1	1	2	4	3	0.028	0.099	0.320	0.410	0.143	4
274	2	1	1	4	3	2	0.015	0.057	0.229	0.461	0.238	4
275	2	1	3	2	4	2	0.021	0.074	0.273	0.444	0.188	4
284	1	1	1	4	4	3	0.027	0.094	0.312	0.417	0.149	4
291	1	1	1	4	4	3	0.027	0.094	0.312	0.417	0.149	4
292	1	1	3	2	4	2	0.027	0.094	0.312	0.417	0.150	4
293	1	2	3	1	1	1	0.194	0.350	0.325	0.111	0.020	2
294	1	1	1	3	4	3	0.032	0.108	0.334	0.396	0.130	4
295	2	1	1	3	4	3	0.019	0.068	0.258	0.451	0.204	4
296	2	1	2	5	4	3	0.026	0.090	0.304	0.424	0.157	4
299	1	1	1	3	4	2	0.011	0.042	0.184	0.461	0.302	4
300	2	2	2	3	4	2	0.027	0.094	0.312	0.417	0.150	4
307	1	1	3	1	4	3	0.086	0.232	0.403	0.229	0.049	3
310	1	2	4	1	3	3	0.392	0.370	0.185	0.046	0.008	1
318	1	2	2	1	1	1	0.143	0.310	0.368	0.151	0.029	3
332	1	2	1	3	3	2	0.051	0.159	0.386	0.321	0.084	3

4.4.3 H2: Single Factor Modification

A single factor modification is defined as a change to a single IP factor while all other factors are held constant. This modified factor is applied to all projects in the validation dataset. For example, the PM could require that both Technical and Mission Management must review and provide feedback to all project proposals (i.e., Feedback Author = 4). In the DST, this IP factor would then be set to '4' for all projects.

Using the DST, the effect of individually modifying each factor was determined and the results provided in Table 4-9. There are 21 total single factor modifications that were performed with the DST, one for each possible level within each factor. In the original validation dataset of 40 projects, 34 of the projects had a Project Rating of 3 or greater. Fifteen of the single factor modifications increased the number of projects rated at 3+ to be greater than 34, whereas five modifications resulted in a decrease and one modification left the dataset unchanged. The distribution of Project Ratings for the original validation dataset as well as the best performing modification for each factor are provided in Figure 4-13. Although the modifications all improve the portfolio Project Ratings, only two of the modifications (PI IRAD Experience = 3; Revision Process = 1) result in at least one Project Rating equal to 5.

Table 4-9. Number of projects with a 3+ Project Rating at each factor level.

Factor Level	PI IRAD Experience	PI-Org Alignment	Team Missing	Expenditure	Feedback Author	Revision Process
1	34	35	40 *	36	12 *	39 *
2	36 *	30 *	37	38 *	30 *	35 *
3	39 *	--	31 *	39 *	39	31 *
4	--	--	27 *	39 *	39 *	--
5	--	--	--	39 *	--	--

'*' = Modified Project Rating has a statistically different median than original Project Rating

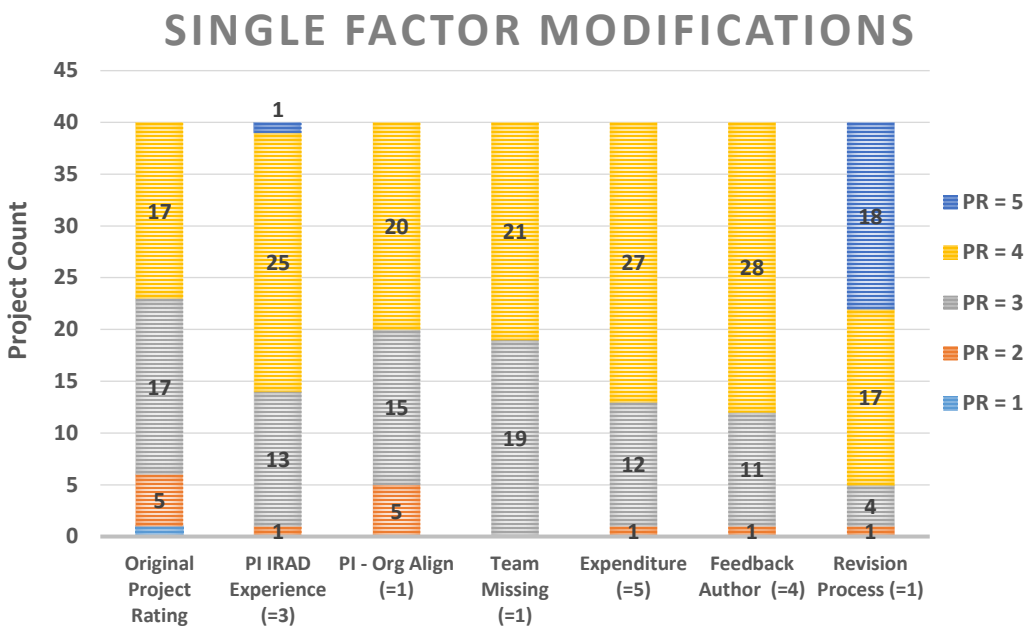


Figure 4-13. Project Rating distributions for best-case single factor modifications.

The Wilcoxon Signed Rank Test for Matched Pairs was performed on the set of modified Project Ratings to determine if the medians were significantly different than the median of the original ratings. The factor modifications that result in statistically significant differences are noted in Table 4-9 with an asterisk (*). Sixteen of the 21 single factor modifications resulted in a significantly different set of Project Ratings.

The criteria for satisfying H2 require that all projects must reach a 3+ Project Rating and the difference between the medians for the original and modified dataset should be statistically significant. Of the 21 single factor modifications that are possible, only one case satisfies both criteria, which is setting Team Missing to 1 (i.e., all proposed team members worked on the project). For this modification, all 40 tests are rated at 3+ (Table 4-9) and the medians of the original and modified Project Ratings are statistically different (p-value = 0.000). This result satisfies H2.

4.4.4 H2: Multiple Factor Modification

Although the single factor modification satisfied H2, the ability to modify multiple IP factors concurrently will provide more potential options for an organization to consider when determining how to improve Project Ratings. The DST can be used to explore combinations of factor modifications and their impact on project success.

A practical multiple factor modification was designed and evaluated. Guiding limitations were placed on this design, including no increased expenditures and any changes to existing proposal solicitation and selection processes must be minimized. The new IP design prescribed three factor modifications: i) require all proposal feedback to include both Mission and Technical Management (Proposal Feedback = 4), ii) ensure that the PI works within the funding organization (PI – Organization Alignment = 1) and iii) require that the PI has previously managed at least one research project (PI IRAD Experience = 2 or 3). The DST was used to make these changes and then calculate the new Project Rating for all 40 projects.

The resulting Project Rating distribution is provided in Figure 4-14. The distribution shows that all 40 projects now have a rating of 3 or greater. Additionally, the changes to the Project Rating for these factors resulted in a statistically significant difference when compared with the median of the original distribution using the Wilcoxon Signed Rank Test for Matched Pairs ($p = 0.000$). This result also satisfies H2.

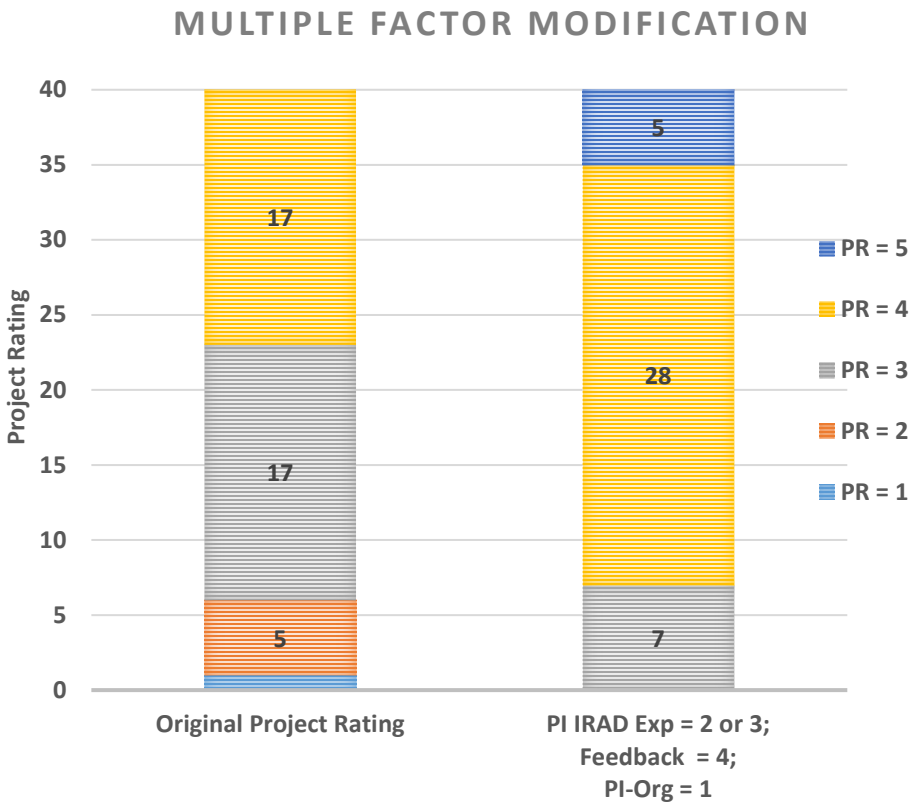


Figure 4-14. Project Rating distributions for multiple factor – multiple level changes.

4.5 Summary

In summary, this praxis analyzed a dataset of 479 projects, each characterized by 36 Innovation Process factors and a single Project Rating. An OLR model relating IP factors to Project Rating was successfully trained on 334 of these projects and then tested against the remaining dataset. The final OLR model had six significant factors, thus satisfying H1. This model was then used as the basis for a DST that was subsequently built and validated. The validation occurred by evaluating the ability of factor changes to significantly modify the population mean for Project Rating and get all projects above a 3+ predicted rating. For single level factor modifications, one case satisfied H2. In an

additional modification permitting two-factor modifications, the specific case examined also satisfied H2. As a result, both H1 and H2 were satisfied.

Chapter 5—Discussion and Conclusions

5.1 Discussion

The Innovation Process (IP) is the framework used to facilitate all phases of a research project, including concept solicitation, selection, management, and transition to application. This research explored the impact of the IP factors on project success and developed a Decision Support Tool (DST) to assist Portfolio Managers (PMs) in designing an IP that will maximize that success.

5.1.1 H1 Discussion

The first hypothesis developed as part of this research states:

H1: Five factors impact the likelihood of project success: Proposal Revision Process, Feedback Author, Principal Investigator Experience, Team Composition and Funding Level.

To investigate H1, thirty-six IP factors and a single response (Project Rating) were collected for 479 Independent Research and Development (IRAD) projects performed at the Johns Hopkins University Applied Physics Laboratory (APL). The project dataset was partitioned into training and testing data. Using Ordinal Logistic Regression (OLR), thirty factors were eliminated for lack of statistical significance ($p<0.05$). The remaining six IP factors (Table 4-5) were: PI IRAD Experience, PI-Org. Alignment, Team Missing, Expenditure, Feedback Author, and Revision Process. These six factors were included in the final OLR model. Since the model construct included the five factors from H1, along with one additional factor (PI – Organization Alignment), H1 was satisfied.

Two of the significant factors, Feedback Author and Revision Process, occur during the proposal solicitation phase, which is the first stage of the IP. Model results indicate that providing proposal feedback to the PI is important to eventual project success. More specifically, choosing to include both mission and technical management in the feedback process maximizes project success for that factor. Alternative feedback options (mission management only, technical management only or crowdsourcing) also improve project success when compared with no feedback, but at a reduced magnitude. Therefore, the opportunity for the PI to gain management feedback early in the IP process (i.e., the proposal stage) is key to project success. Additionally, the model indicates that the most beneficial feedback format is actually including open, informal engagement between the PI and management as part of the proposal revision process.

The remaining four significant IP factors are impactful during the management phase of the IP. Two of these factors, PI IRAD Experience and PI – Organization Alignment, consider characteristics of the PI. The more experience the PI has in leading projects, the greater the likelihood of the project being successful. Per the proportional odds calculated from the OLR, a PI with no prior experience leading a project is 0.76 times as likely to achieve success as compared to a PI that has led at least 1 prior project. Additionally, a PI that works directly for the organization that is funding the research is 2.23 times as likely to have a successful project then a PI that does not work directly within the funding organization.

Project Expenditure was also included in the OLR model. As the cost of the project increases, so does the likelihood that the results of the project will successfully transition. While this correlation may seem obvious, the relative level of impact that

expenditures have on the project can be compared with the impact of other factors. This information is useful as a PM considers IP factor modifications and the associated cost of implementing those modifications. For example, if simple changes to the proposal review process have the same effect on project success as doubling project investment, then the more economical modification will be more attractive.

The final significant factor focused on the number of team members who were included in the proposal but never actually contributed to the project, Team Missing. The difference between the proposed team and the actual team to execute the research may be due to a number of factors, including lack of team member availability, changing staffing needs or poorly formed staffing plans. Regardless, the greater the number of planned team members that never actually support the effort, the more the likelihood of project success is negatively impacted.

Performance of the final OLR model was evaluated using the test data. The model demonstrated exact Project Rating predictions for 40.7% of the projects and was within one level for 82.1% of the projects. Project Rating predictions that occur within one level provide a closeness measurement which, when compared with exact matches for OLR models, has been considered a comparable, and potentially better, general assessment of performance (Lu, 2019). The constructed model will be quite effective in determining if a project achieves a Project Rating of 3 or greater, indicating the likelihood that the project transitions to future investment.

5.1.2 H2 Discussion

The second hypothesis developed as part of this research states:

H2: Implementing changes identified by the decision support tool (DST) will improve all project success ratings to 3 or more.

In response to H2, a DST was developed to determine the impact of IP factor modifications on improving project success and if that improvement was sufficient to raise all Project Ratings to 3 or greater. The trained and tested OLR model was implemented within the DST. Validation of the DST efficacy was then determined by systematically modifying the IP factor levels for a subset of forty projects.

A series of single factor modifications were used to determine the impact of changing each factor level on the likelihood of project success (Table 4-9). Using the Wilcoxon Signed Rank Test for Matched Pairs, fifteen of the twenty-one modifications indicated a statistically significant improvement between the modified Project Ratings and the original ratings. However, one of these modifications also produced a result where all forty projects were now rated at 3 or greater. This specific case occurred when Team Missing was at a level of 1. This indicates that none of the projects can be missing any team member that was originally part of the proposed team. While this result satisfies H2, this condition may be hard to meet for all projects or organizations. Therefore, other IP designs that satisfy H2 were sought.

The modification of multiple IP factors concurrently would greatly increase the flexibility in customizing IP designs and increase general DST utility to differing organizations. Therefore, the DST was used to explore combinations of factor modifications. A specific factor combination was designed and tested with the goals of

keeping project expenditures constant and minimizing changes to existing proposal solicitation and selection processes. The selected modification required integrated proposal reviews and feedback (Proposal Feedback = 4), all PIs must work in the funding organization (PI-Org. = 1) and PIs must have led at least one prior project (PI Exp. = 2 or 3). The DST was used to make these changes, which resulted in a statistically significant improvement in project likelihood of success, with all ratings at 3 or greater. This multiple factor modification satisfied H2 and demonstrated that unique combinations of factor changes could be tailored to an organization's preferences.

To actually implement the IP described in this scenario, the factor modifications must be considered within an organization's processes. For the factor levels specified above, the first modification can be accommodated by instituting an integrated proposal review process that brings together both the technical and mission management. The second and third conditions cannot be satisfied if the proposal solicitation allows for any staff member in the larger enterprise to participate. However, a PM could take steps to satisfy the IP factor level in other ways. For example, the second factor (PI-MA Alignment) and third factor (PI Experience) modifications could potentially be satisfied by using senior technical mentors. If the PI is inexperienced and from another organization, then a senior technical mentor from within the funding organization, with a history of successful research project leadership experience, could be assigned to closely assist the PI during their tenure leading the project.

To take this implementation analysis one step further, the validation dataset (40 projects) would require a mentor for 22 PIs, nine of whom would be assisting a PI that is outside of their home organization. Four projects would need to shift away from

crowdsourcing feedback and go to technical and mission management reviews, while 8 projects would need to add technical management and 6 would need to add mission management to the review team. It should be noted that these changes could readily be instituted within current APL processes, especially since many of these specific IP approaches are already instituted within some parts of the enterprise.

5.1.3 DST Impact

The 479 project dataset analyzed in this Praxis contained 149 unique combinations of the six significant IP factors. Although all IRAD projects were performed within just six different organizations at APL, this level of diversity suggests that either a substantial level of IP customization is required for each project or that the PMs require better methods by which to identify important factors and design them into an IP that best suits their organizations. Either of these scenarios confirms the need for an effective DST that can support the PM and provide them with the basis for maximizing the likelihood of project success. This praxis has created and validated such a tool.

During the four years of data collected for this praxis, 23 projects were stopped and 76 failed to transition. As a result, 99 projects did not have follow-on activities, which equates to $17M in research investment. With the DST, each PM will now be able to assess the likelihood of project success, modify their IP to maximize that success and therefore increase the return on research investment.

5.2 Conclusions

This praxis has successfully described how IP factors impact the likelihood of project success and developed a tool to modify the IP for maximizing that success. OLR methods were used to identify six IP factors that are significantly correlated to successful

project outcomes. The OLR model was then implemented as the basis for a decision support tool (DST) capable of aiding a PM in the design or modification of research project IP. Through a series of IP factor modifications, the DST demonstrated the ability to improve the outcomes of a portfolio of projects, thus increasing the number of research projects that transition to future research or application. This DST will be a useful tool for PMs who oversee innovative research projects and would like to design or modify their innovation process. .

5.3 Contributions to Body of Knowledge

This research contributes to the body of knowledge focused on understanding how Innovation Process design can improve research project success and the development of associated tools to aid the portfolio manager in improving their IP. Specific contributions include:

- First known effort to identify the relationship between leading innovation indicators, from all stages of the innovation process, with project success.
- First known database to include both this scale of research projects (479) and the resolution of the innovation process descriptions (36 factors) for each project.
- First validated, outcome-based decision support tool to aid the portfolio manager in the design and modification of the research project innovation process.
- First known effort to demonstrate the impact of an innovation process decision support tool on improving the probability of project success.

5.4 Recommendations for Future Research

This praxis has developed a model which identifies IP factors that impact the likelihood of research project success. Developed using research projects from an R&D organization, this research could be furthered by testing model generalizability to other industries and project types. To examine how well this model may convey to other industries, a similar, high resolution project dataset would need to be established for the industry. The significant IP factors could then be identified and compared to determine if industry-specific differences drive the need for different approaches to the innovation process. This research could also be furthered by conducting longitudinal studies. This praxis included projects from a recent, four-year span of investments. Since the impact of research progress may not often be felt until years after the project is concluded, an annual re-assessment of a prior project's rating may reveal a shifting assessment over time. If this increasing/decreasing of the assessment does occur, then the model could incorporate time as a dimension of the study and inform a PM as to how long a project will take before it contributes to successful outcomes.

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Appendix A

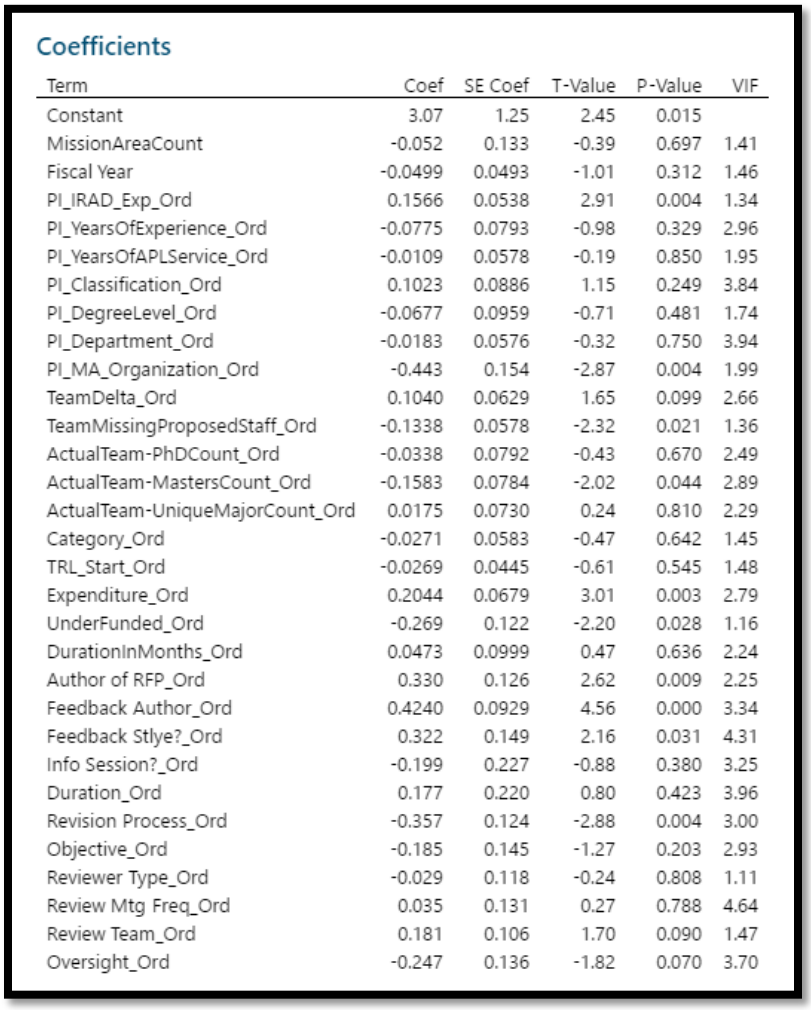
A.1 VIF Results

Minitab results from conducting regression analysis to determine Variance Inflation Factors (VIFs) for each independent factor. The initial assessment (Figure A-1) and the final assessment (Figure A-2) are included below.

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2.83	2.53	1.12	0.263	
MA / Initiative	-0.296	0.114	-2.59	0.010	22.76
MissionAreaCount	-0.014	0.134	-0.11	0.914	1.45
Fiscal Year	-0.0110	0.0539	-0.20	0.838	1.76
PI_IRAD_Exp_Ord	0.1493	0.0538	2.77	0.006	1.36
PI_YearsOfExperience_Ord	-0.0825	0.0791	-1.04	0.297	2.96
PI_YearsOfAPLService_Ord	-0.0081	0.0581	-0.14	0.889	1.98
PI_Classification_Ord	0.1145	0.0891	1.29	0.199	3.91
PI_DegreeLevel_Ord	-0.0875	0.0962	-0.91	0.364	1.76
PI_Department_Ord	-0.0173	0.0634	-0.27	0.785	4.80
PI_MA_Organization_Ord	-0.371	0.165	-2.24	0.025	2.30
ActualTeamSize_Ord	0.0273	0.0971	0.28	0.779	5.90
TeamDelta_Ord	0.0911	0.0710	1.28	0.200	3.42
TeamMissingProposedStaff_Ord	-0.1387	0.0586	-2.37	0.018	1.41
ActualTeam-PhDCount_Ord	-0.0265	0.0839	-0.32	0.752	2.82
ActualTeam-MastersCount_Ord	-0.1505	0.0868	-1.73	0.084	3.57
ActualTeam-UniqueMajorCount_Ord	0.0143	0.0750	0.19	0.848	2.44
Category_Ord	-0.0222	0.0587	-0.38	0.706	1.48
TRL_Start_Ord	-0.0305	0.0446	-0.68	0.495	1.50
Expenditure_Ord	0.2044	0.0704	2.90	0.004	3.03
UnderFunded_Ord	-0.282	0.122	-2.31	0.021	1.17
DurationInMonths_Ord	0.038	0.100	0.38	0.703	2.25
Author of RFP_Ord	0.067	0.259	0.26	0.796	9.55
Response Format_Ord	-0.297	0.180	-1.65	0.100	23.03
Feedback Cycles_Ord	0.819	0.446	1.83	0.067	20.29
Feedback Author_Ord	0.379	0.169	2.25	0.025	11.10
Feedback Stlye?_Ord	0.792	0.296	2.67	0.008	17.24
Info Session?_Ord	-0.203	0.276	-0.73	0.464	4.87
Duration_Ord	0.762	0.318	2.40	0.017	8.30
Revision Process_Ord	-0.603	0.193	-3.13	0.002	7.31
Objective_Ord	-0.266	0.155	-1.72	0.087	3.38
Reviewer Type_Ord	-0.024	0.186	-0.13	0.898	2.78
Selection Method_Ord	-0.037	0.475	-0.08	0.939	45.50
Review Mtg Freq_Ord	0.056	0.134	0.42	0.674	4.90
Review Team_Ord	0.186	0.107	1.75	0.081	1.49
Oversight_Ord	-0.335	0.142	-2.35	0.019	4.08

Figure A-1. Initial VIF results for IP factors.



Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	3.07	1.25	2.45	0.015	
MissionAreaCount	-0.052	0.133	-0.39	0.697	1.41
Fiscal Year	-0.0499	0.0493	-1.01	0.312	1.46
PI_IRAD_Exp_Ord	0.1566	0.0538	2.91	0.004	1.34
PI_YearsOfExperience_Ord	-0.0775	0.0793	-0.98	0.329	2.96
PI_YearsOfAPLService_Ord	-0.0109	0.0578	-0.19	0.850	1.95
PI_Classification_Ord	0.1023	0.0886	1.15	0.249	3.84
PI_DegreeLevel_Ord	-0.0677	0.0959	-0.71	0.481	1.74
PI_Department_Ord	-0.0183	0.0576	-0.32	0.750	3.94
PI_MA_Organization_Ord	-0.443	0.154	-2.87	0.004	1.99
TeamDelta_Ord	0.1040	0.0629	1.65	0.099	2.66
TeamMissingProposedStaff_Ord	-0.1338	0.0578	-2.32	0.021	1.36
ActualTeam-PhDCount_Ord	-0.0338	0.0792	-0.43	0.670	2.49
ActualTeam-MastersCount_Ord	-0.1583	0.0784	-2.02	0.044	2.89
ActualTeam-UniqueMajorCount_Ord	0.0175	0.0730	0.24	0.810	2.29
Category_Ord	-0.0271	0.0583	-0.47	0.642	1.45
TRL_Start_Ord	-0.0269	0.0445	-0.61	0.545	1.48
Expenditure_Ord	0.2044	0.0679	3.01	0.003	2.79
UnderFunded_Ord	-0.269	0.122	-2.20	0.028	1.16
DurationInMonths_Ord	0.0473	0.0999	0.47	0.636	2.24
Author of RFP_Ord	0.330	0.126	2.62	0.009	2.25
Feedback Author_Ord	0.4240	0.0929	4.56	0.000	3.34
Feedback Stlye?_Ord	0.322	0.149	2.16	0.031	4.31
Info Session?_Ord	-0.199	0.227	-0.88	0.380	3.25
Duration_Ord	0.177	0.220	0.80	0.423	3.96
Revision Process_Ord	-0.357	0.124	-2.88	0.004	3.00
Objective_Ord	-0.185	0.145	-1.27	0.203	2.93
Reviewer Type_Ord	-0.029	0.118	-0.24	0.808	1.11
Review Mtg Freq_Ord	0.035	0.131	0.27	0.788	4.64
Review Team_Ord	0.181	0.106	1.70	0.090	1.47
Oversight_Ord	-0.247	0.136	-1.82	0.070	3.70

Figure A-2. Final VIF results for IP factors.

A.2 Ordinal Logistic Regression Training Results

Minitab results from ordinal logistic regression simulations on the training data for backward elimination and forward selection step-wise model construction methods.

Ordinal Logistic Regression: Assessment S versus PI Irad ... Alignm, ...

Link Function: Logit

Response Information

Variable	Value	Count
Assessment SCORE	1	19
	2	49
	3	108
	4	116
	5	42
	Total	334

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	-4.13772	0.722262	-5.73	0.000			
Const(2)	-2.62481	0.686212	-3.83	0.000			
Const(3)	-1.06131	0.671536	-1.58	0.114			
Const(4)	0.849795	0.678259	1.25	0.210			
PI Irad Exper.	-0.253911	0.115326	-2.20	0.028	0.78	0.62	0.97
PI-MA Alignment	1.14423	0.295625	3.87	0.000	3.14	1.76	5.60
Expenditure	-0.239211	0.101510	-2.36	0.018	0.79	0.65	0.96
Revision Process							
2	0.516830	0.493256	1.05	0.295	1.68	0.64	4.41
3	1.04951	0.476754	2.20	0.028	2.86	1.12	7.27

Log-Likelihood = -465.890

Test of All Slopes Equal to Zero

DF	G	P-Value
5	28.639	0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	171.798	211	0.978
Deviance	179.070	211	0.946

Measures of Association:

(BetweentheResponseVariableandPredictedProbabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	24373	59.5	Somers' D	0.24
Discordant	14456	35.3	Goodman-Kruskal Gamma	0.26
Ties	2126	5.2	Kendall's Tau-a	0.18
Total	40955	100.0		

Figure A-3. Model 1: OLR results for backward elimination method.

Ordinal Logistic Regression: Assessment S versus PI Irad ... Alignm, ...

Link Function: Logit

Response Information

Variable	Value	Count
Assessment SCORE	1	19
	2	49
	3	108
	4	116
	5	42
	Total	334

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Const(1)	-4.01453	0.891570	-4.50	0.000			
Const(2)	-2.41166	0.868474	-2.78	0.005			
Const(3)	-0.699088	0.861207	-0.81	0.417			
Const(4)	1.30603	0.861395	1.52	0.129			
PI Irad Exper.	-0.268255	0.116603	-2.30	0.021	0.76	0.61	0.96
PI-MA Alignment	0.801712	0.298736	2.68	0.007	2.23	1.24	4.00
Expenditure	-0.159999	0.0968399	-1.65	0.098	0.85	0.70	1.03
Team Missing	0.368349	0.119423	3.08	0.002	1.45	1.14	1.83
Feedback Author	-0.754584	0.151774	-4.97	0.000	0.47	0.35	0.63
Revision Process	1.06327	0.210659	5.05	0.000	2.90	1.92	4.38

Log-Likelihood = -449.273

Test of All Slopes Equal to Zero

DF	G	P-Value
6	61.872	0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	520.298	534	0.656
Deviance	446.034	534	0.998

Measures of Association:

(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	27328	66.7	Somers' D	0.35
Discordant	12913	31.5	Goodman-Kruskal Gamma	0.36
Ties	714	1.7	Kendall's Tau-a	0.26
Total	40955	100.0		

Figure A-4. Model 2: OLR results for forward selection method.

A.3 Wilcoxon Signed Rank Test Results

Minitab results examining the statistically significant differences between the set of projects before and after IP factor level changes.

Wilcoxon Signed Rank Test: PI Exp 2, PI Exp 3, PI-MA 1, ... ev Process 3

Method

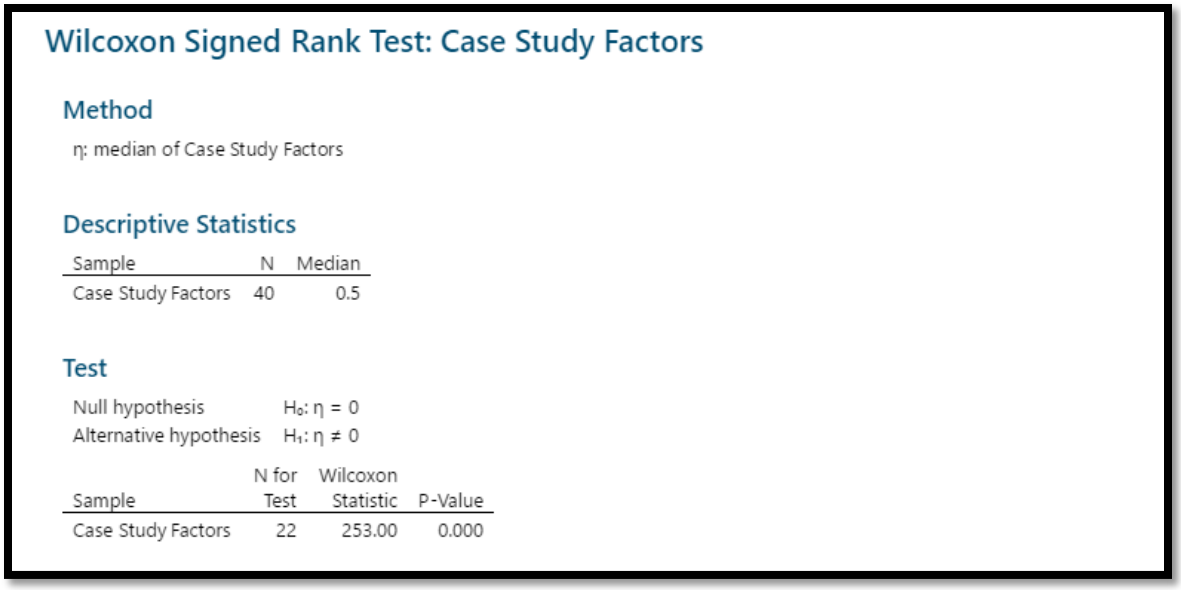
η: median of PI Exp 2, PI Exp 3, PI-MA 1, PI-MA2, Team Miss 1, ...

Test

Null hypothesis	$H_0: \eta = 0$
Alternative hypothesis	$H_1: \eta \neq 0$

Sample	N for Test	Wilcoxon Statistic	P-Value
PI Exp 2	7	28.00	0.022
PI Exp 3	16	136.00	0.000
PI-MA 1	5	15.00	0.059
PI-MA2	20	10.50	0.000
Team Miss 1	10	55.00	0.006
Team Miss 2	9	25.00	0.813
Team Miss 3	12	6.50	0.012
Team Miss 4	21	0.00	0.000
Expend 1	9	25.00	0.813
Expend 2	11	66.00	0.004
Expend 3	12	78.00	0.003
Expend 4	14	105.00	0.001
Expend 5	16	136.00	0.000
Feed Author 1	31	0.00	0.000
Feed Author 2	21	11.00	0.000
Feed Author 3	22	103.50	0.465
Feed Author 4	16	136.00	0.000
Rev Process 1	32	528.00	0.000
Rev Process 2	18	133.00	0.041
Rev Process 3	10	0.00	0.006

Figure A-5. Wilcoxon Signed Rank Test for Single Factor Modifications.



Wilcoxon Signed Rank Test: Case Study Factors

Method

η: median of Case Study Factors

Descriptive Statistics

Sample	N	Median
Case Study Factors	40	0.5

Test

Null hypothesis	$H_0: \eta = 0$
Alternative hypothesis	$H_1: \eta \neq 0$

Sample	N for Test	Wilcoxon Statistic	P-Value
Case Study Factors	22	253.00	0.000

Figure A-6. Wilcoxon Signed Rank Test for Multiple Factor Modification.