The Evaluation of Uncertainty in the Early Phases of Project Management

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The Evaluation of Uncertainty in the Early Phases of Project Management

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Dedication

I admire the Stark family's ability to use turn of phrases. With that in mind, to my family "I love you 3,000" (Russo and Russo, 2019, 00:41:16) for being as dedicated towards my endeavors as me. To my dad, "Dead almost 20 years, you're still taking me to school" (Favreau, 2010, 01:23:16). It's been over 13 years, but you continue to inspire me.

Favreau, J. (Director). (2010). Ironman 2 [Film]. Marvel Studios.

Russo, A. and Russo, J. (2019). Avengers: Endgame [Film]. Marvel Studios.

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Praxis Abstract

The Evaluation of Uncertainty in the Early Phases of Project Management

This praxis explored project schedule uncertainty and developed a framework to prioritize risk and opportunity management. A robust literature review was performed to explore terms lacking industry-standard definitions like *ambiguity*, *uncertainty*, *risk*, and *opportunity*. The praxis framework took inspiration from Decision-Making under Deep Uncertainty (DMDU) methods to reimagine network diagrams, which was not found to be widely applied in the project management literature review. It coupled the deterministic (i.e., DMDU) analysis with a statistical analysis (i.e., Program Evaluation Review Technique [PERT]) to provide schedule bookends, and it developed a proof-of-concept computational tool to facilitate the analysis.

The praxis framework was tested using a case study network diagram. The analysis of the statistical and deterministic information resulted in a prioritized activity list that could be used by a practitioner, in conjunction with project information, to prioritize risk management activities. This is especially helpful in cases where project schedule and budget limitations exist. The praxis framework does not promote a specific type of risk analysis; however, it helps risk management by providing recommendations to link the praxis framework results and risk analysis and discusses best practices for developing measurable risks.

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List of Symbols/Nomenclature

1. DAPP Dynamic Adaptive Policy Pathways
2. DMDU Decision-Making Under Deep Uncertainty
3. NPD New Product Development
4. PERT Program Evaluation and Review Technique
5. PMBOK Project Management Book of Knowledge
6. PMI Project Management Institute
7. RDM Robust Decision-Making
8. RMP Risk Management Process
9. VaR Value at Risk

List of Equations

1. Equation 1 PERT Activity Expected Value
2. Equation 2 PERT Activity Standard Deviation
3. Equation 3 Activity Variance
4. Equation 4 Total Project Standard Deviation
5. Equation 5 Triangular Distribution Expected Value
6. Equation 6 Triangular Distribution Variance
7. Equation 7 Activity Probability
8. Equation 8 Risk & Opportunity Score

Glossary of Terms

Activity Probability: The number of network pathways an activity is present divided by the total number of network pathways evaluated.

Ambiguity: Not knowing what you don't know (Levardy and Browning, 2009).

Critical Path: A project's longest path. The associated duration often determines the project length (Pinto, 2020).

Critical Path Method: A method to estimate the critical path and evaluate schedule flexibility (PMI, 2021).

Criticality Index: The probabilities that activities are on the critical path. The data can be obtained from a Monte Carlo analysis, and collectively they identify the probability of network project completion paths being the critical path (Van Slyke, 1963).

Decision-Making Under Deep Uncertainty: DMDU provides concepts, tools, and multi-objective, multi-scenario decision support methods designed to inform and improve decisions that face such conditions (RAND, 2024).

Delay Impact Score: The average of an activity's percentage of critical path results.

Opportunity: An event that, if it occurs, will have a positive effect on the project. Opportunity can be represented through probability of occurrence and consequence. The opposite of opportunity is risk (adapted from PMI, 2021; Levardy and Browning, 2009).

Program Evaluation Review Technique: An estimation technique that uses optimistic, pessimistic, and most likely estimates to account for project activity uncertainty (Pinto, 2020).

Risk: An event that, if it occurs, will have a negative effect on the project. Risk can be represented through probability of occurrence and consequence. The opposite of risk is opportunity (adapted from PMI, 2021; Levardy and Browning, 2009).

Activity Delay Risk: The *Activity Probability* multiplied by the *Delay Impact Score*.

Total Project Uncertainty: The totality of project risk and opportunity.

Uncertainty: Knowing what you don't know (Levardy and Browning, 2009). Uncertainty includes both opportunities and risks (Kolltveit et al., 2004).

Chapter 1: Introduction

1.1 Background

The failure to properly evaluate uncertainty early in the project management process is a problem in industries like engineering, construction, and technological innovation. The project management profession has matured over time, and methods exist for evaluating project schedule uncertainty. Examples include the critical path method that identifies critical activities to a project schedule. However, in its simplest form, only one project schedule is evaluated. The Program Evaluation and Review Technique (PERT) and Monte Carlo Simulation model activity and project schedule times using statistical distributions to provide a range of completion times.

According to Marzi et al. (2021), research into the new product development (NPD) process has continued to grow over the last 30 years, reflecting the importance that continues to be placed on this research type. The NPD field is a good field of study to examine uncertainty since it is often managed through a project or product management process. Statistical methods require defining the distribution(s) parameters, and these parameters are often estimated based on incomplete information. The result is a statistical distribution(s) that may not fully describe the project's schedule uncertainty, which adversely impacts project cost, schedule, and/or performance.

1.2 Research Motivation

This praxis research begins with a literature review to define project uncertainty since an industry-standard definition does not exist, and provides a delineation between uncertainty and another term, ambiguity. There is extensive literature surrounding the problem of defining these terms, yet they continue to stifle the project management

profession. For example, Assaad et al. (2020) cited a global construction survey completed by KPMG (2015; as cited in Assaad et al., 2020) that showed only 31% of construction projects were performed within 10% of their budget. Additionally, only 25% of projects were completed within 10% of their original deadlines. The paper also cited information from the Project Management Institute (2017; as cited in Assaad et al., 2020) that despite cost and schedule overruns, only 28% of companies use project performance techniques.

This praxis explores elements of Decision-Making under Deep Uncertainty (DMDU) to develop a prioritized activity list and guide risk and opportunity management early in the project management process. This prioritized list has the practical application of helping practitioners determine where to focus risk and opportunity management activities in cases of schedule and budget resource constraints. The DMDU methods are used to evaluate problems in areas such as climate change, health policy, and transportation (RAND Corporation, 2024), and for this praxis its methods complement the statistical methods traditionally used for schedule analysis. A praxis goal is that it contributes to the body of knowledge surrounding the management of project uncertainty.

1.3 Problem Statement

The praxis problem statement is below.

The failure to properly consider and quantify uncertainty early in the project management process results in too many late, overbudget, not fully successful, and/or failed projects.

To provide examples of the problem statement wording *too many late, overbudget, not fully successful, or failed projects*, Lévárdy and Browning (2009) cited a survey

completed by The Standish Group (2001) of over 250,000 small software product development products. The authors reported that 23% of the products failed; 49% were either late, overbudget, or had fewer features or functions than originally scoped; and 28% succeeded. Along with the information provided in Section 1.2 (Research Motivation), these statistics provide justification to better define and improve the evaluation of project schedule uncertainty.

1.4 Thesis Statement

The praxis thesis statement is below.

A structured methodology integrated with a consistent decision-support evaluation tool will effectively assess uncertainty and reduce the number of late, overbudget, not fully successful, and/or failed projects.

This praxis focused on a literature review to explore terms lacking industry-standard definitions like *ambiguity*, *uncertainty*, *risk*, and *opportunity*. It developed a methodology (i.e., framework) to evaluate project uncertainty that provides a prioritized activity list to focus risk and opportunity management decisions. The work was completed using a proof-of-concept decision-support tool in Microsoft Excel, but the framework could be implemented using other software tools.

1.5 Research Objectives

The praxis research objectives are below.

Research Objective 1: Develop an evaluation methodology early in the project management process that incorporates uncertainty and DMDU methodology elements.

Research Objective 2: Complement the definitions and DMDU elements with a statistical analysis to provide greater resolution into the project uncertainty analysis.

Research Objective 3: Develop a decision-support tool to model network diagrams using the DMDU and statistical methodology; analyze, document, and couple the results, with risk and opportunity recommendations.

1.6 Research Questions and Hypotheses

The praxis research questions, and corresponding hypotheses, are below.

Research Question 1: How can definitions and DMDU methods (e.g., Dynamic Adaptive Policy Pathways) be applied early in the project management process to evaluate project uncertainty?

Research Question 2: How can a task- and project-level statistical analysis (e.g., PERT and Monte Carlo Simulation) be incorporated with DMDU methods in the project uncertainty evaluation?

Research Question 3: How can a decision-support tool that is informed by the DMDU and statistical methods facilitate development of project risk and opportunity recommendations?

Hypothesis 1: The DMDU methodology, coupled with definitions, can be applied to a project network analysis to evaluate project schedule uncertainty.

Hypothesis 2: A statistical analysis can be integrated with the DMDU methodology to evaluate project uncertainty.

Hypothesis 3: The DMDU and statistical methodologies can be linked with a decision-support tool to prioritize project activities that feed an activity-level risk and opportunity analysis.

1.7 Scope of Research

This praxis will add to the body of knowledge surrounding the evaluation of project uncertainty early in the project management process by evaluating the effectiveness of DMDU as it relates to project uncertainty. The DMDU methods seem applicable to uncertainty evaluation in project management, but the author found little evidence of their implementation in the field. Additionally, while the problem statement's description cites software product development projects, per the problem statement this praxis research will develop information that can be broadly applied to project management.

Project uncertainty can be difficult to quantify, but risk statements can help with this problem. Even simple risk analysis tools that use subject matter expertise to develop a risk statement, and corresponding probability and consequence, can be a useful tool to screen, prioritize, and make decisions about how to move forward in a project. Kaplan and Garrick (1981) provided an example on how to quantitatively define risk through the idea of a *set of triplets*. For a given risk, the triplet represents the scenario, probability, and consequence. By representing the probability as a probability curve, the triplet includes uncertainty in frequency. This praxis research will align with the risk analysis process by providing activity prioritization information to complement risk and opportunity management early in the project management process.

1.8 Research Limitations

The research presented in this praxis has limitations. First, the data used for this praxis was acquired from existing publications. This means the data are not tied to a specific industry, nor were they evaluated in real-time during the project management process.

Second, since the author did not find widespread use of DMDU in the project management field, this praxis is focused on methodology development with less focus placed on decision-support tool development. The decision-support tool presented in this praxis was effective to perform proof-of-concept, but further refinement could produce a more user-friendly, holistic, and automated decision-support tool.

Third, the praxis focused on the development of a decision-support framework that could help prioritize risk and opportunity management, but the effectiveness of the framework in improving project performance was not measured. Additional work through practitioner feedback, empirical testing, the application to a real project, and/or other methods could provide useful data to quantify the framework's value in project, engineering, and risk and opportunity management. This is further explored in Section 5.3 (Future Research).

1.9 Organization of Praxis

This praxis is organized into five chapters, described below. A praxis abstract is provided prior to Chapter 1, and references and permissions information, respectively, are provided after Chapter 5.

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: Methodology

Chapter 4: Results

Chapter 5: Discussion & Conclusion

Chapter 2: Literature Review

2.1 Introduction

This praxis chapter's literature review is organized into five topic areas, excluding the introduction. The first two topic areas provide discussions on how literature has defined risk and ambiguity and uncertainty, respectively. The third topic area introduces Decision-Making under Deep Uncertainty through a methodology discussion and case study review from other disciplines. The fourth topic area presents statistical applications, and the last topic area reviews literature associated with methods development for evaluating project uncertainty in engineering management. The chapter ends with praxis definitions for risk, ambiguity, and uncertainty.

2.2 Risk

2.2.1 Risk Definition

There is a strong body of literature surrounding the topics of risk and risk management from many industries. Described in Chapter 1 (Introduction), Kaplan and Garrick (1981) proposed a risk definition surrounding the *set of triplets* idea, and Kaplan (1997) stressed again at the 1996 Annual Meeting of the Society for Risk Analysis the importance of consistent language for risk analysis. Additionally, Haimes (2009) discussed the importance of the set of triplets while acknowledging that a universal definition for risk has been difficult to develop, citing the 13 definitions originally proposed by the Society for Risk Analysis and the additional definitions developed since then.

When discussing the difficulty in defining risk, Andretta (2014) cited the same 13 definitions from the 1987 Society for Risk Analysis. Moreover, the author discusses how a universal definition of risk has not been established and presents the idea that some of the difficulty is due to a focus on *what* and not on *assessing* or *measuring it*. To assist this problem, systems theory and the theory of probability were used to define risk, and information on physical quantities were applied to quantitative measurement.

The Project Management Institute (PMI) has developed many tools and techniques to help with project management, including in the risk management topic area. The PMI (2021) defines risk as "an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives" (p. 248). The definition continues through defining positive and negative risks as opportunities and threats, respectively. Furthermore, PMI (2021) notes that risks are "an aspect of uncertainty" (p. 122) and defines overall project risk as "the effect of uncertainty on the project as a whole, arising from all sources of uncertainty" (p. 123).

Hubbard (2020) noted that multiple organizations use risk to represent both positive and negative outcomes. The author describes that this is different from how many industries (e.g., insurance and engineering) define risk as representing a negative outcome, and they provide a long and short definition for risk. The long definition for risk is "a potential loss, disaster, or other undesirable event measured with probabilities assigned to losses of various magnitudes" (p. 26-28); the short definition is "the possibility that something bad could happen" (p. 26-28). These definitions recognize risk as a negative outcome only.

Zhang (2011) categorized risk into two schools: *"*risk as an objective fact" (p. 5) and "risk as a subjective construction" (p. 6) and argued that the definition, management methods, and policies tend to be different between the two schools. The article acknowledges that risk is "not a consistent concept" (p. 5), that "[d]ifferent researchers could have different understandings of risk" (p. 5), and that "the definition of risk has always been in dispute in the history of risk research*"* (p. 5).

The evaluation of if project classification can be used to forecast risk events for engineering design projects was evaluated by Yim et al. (2015). The project classifications of compliance, operational, and strategic were evaluated to determine their predictive power for identifying risk events. The results of interviews from 11 engineering design projects indicate that risk type varies by project type, and that this information could assist with customizing risk plans early in the project life cycle to increase project success.

Qazi et al. (2016) noted as part of their research that industry standards for risk management do not consider the interaction of project complexity and risk, and project managers often rely on their past experiences to determine how to deal with risk. To help this problem, the authors proposed a method using Expected Utility Theory and Bayesian Belief Networks to evaluate interdependency between project complexity, complexity induced risks, and project objectives. The authors noted that they define risk as the *known unknowns*, and they define unexpected emerging risks as *unknown unknowns*.

The definitions from Qazi et al. (2016) can be compared to those proposed by Lévárdy and Browning (2009) for ambiguity and uncertainty. In their paper, uncertainty was defined as "knowing what you don't know*"* (p. 600) and ambiguity was defined as

"not knowing what you don't know" (p. 600) (Sarbacker and Ishii, 1997; Scrader et al., 1993; as cited in Lévárdy and Browning, 2009). One way to interpret the comparison of the papers is that while the definitions of the words from the respective papers seem similar, the terminology they are defining is different. This displays the inconsistent way the terms of risk, ambiguity, and uncertainty are defined.

2.2.2 Additional Risk Literature

Risk management processes (RMPs) can be an important tool for project managers, but it can be difficult to know when to implement them in the project's life cycle. Chapman (1997) noted this observation during the development of an RMP. The author concedes that implementing an RMP early in the project life cycle can result in an RMP that is less formal and quantitative, but more strategic and creative. Implementing an RMP later in the project life cycle means many of the opportunities where the RMP may have been useful have passed; therefore, the author recommends earlier implementation.

Browning (2019) discussed how all risk is not equal and developed the definition for *value at risk* (VaR). The VaR was defined as a distribution around a project's goal, with the goal's uncertainty defining the distribution. One side of the distribution represents outcomes that increase the project's *goal value*; the other side of the distribution represents outcomes that reduce the project's goal value. Project managers can use this to understand what actions reduce the project's *anti-value*, the VaR that reduces the project's goal value.

The importance of software development and other information technology projects to businesses was observed by Jiang et al. (2002). The authors discussed the challenges

faced in completing these projects on time and within budget and observed that little progress had been made in risk quantification. The authors proposed an instrument for measuring software development risk and tested this instrument using a survey of 152 participants to help with this problem. A key research contribution was the author's ability to provide information about how software development risk affects system success, and it provides information on where project managers should focus their attention to improve outcomes.

Qazi et al. (2021) noted that uncertainty can manifest either positive (opportunity) or negative (risk) outcomes, and many studies tend to focus on risks. The authors studied how risk attitude affects project risk, opportunity, and expected performance assessments. Results indicated that a project manager's risk attitude influenced the risk and opportunity assessments of a project, and the authors raised questions about the practical effects of ignoring actual risk and opportunity while benchmarking unrealistic performance criteria. This results in a recommendation for the development of a comprehensive uncertainty assessment framework to describe risk attitude, and another recommendation to tailor risk management tools for the differences in risk attitude.

Regev et al. (2006) observed that many methods used in risk management, including the Program Evaluation and Review Technique (PERT) and Monte Carlo simulation, rely on past information to predict future outcomes. They posed the question of what methods are available for use in technological projects when past data is not an appropriate basis for future decisions? In response to this question, the authors proposed a knowledge gap approach to prioritize risk management for parts of the project identified as high-risk.

Kuo and Lu (2013) evaluated how fuzzy multiple criteria decision-making compared to the traditional statistical-based risk analysis approach. The comparison was applied to the metropolitan construction industry, where the author noted construction projects can experience risk from stakeholders, existing structure removal, and existing utility corridors. Because statistical methods require significant amounts of data, and information about metropolitan construction projects is usually only known by a comparatively few individuals, the proposed fuzzy multiple criteria decision-making approach was found preferential. Additional reasons for this conclusion included that the method took advantage of individual risk perception, and the small sample size helped maintain data quality. The author discussed how the process could be used to evaluate a hierarchy of items and help to prioritize high risk factor processes.

The construction industry relies on risk management for projects of all sizes. Sanchez-Cazorla et al. (2016) observed a lack of risk management research in megaprojects. Their bibliometric analysis found that while risk categorization is described as an important part of risk management, they were unable to find consensus on the topic in literature. The authors contributed this to the "complex nature of risk" (p. 85), and they went on to develop nine risk categories based on their bibliometric findings.

Thamhain (2013) argued that, while risk management is difficult for complex projects, the success of these projects is not random, and management of risk is possible. The author promoted the idea that analytical methods for risk management must be supplemented by "adaptive methods that rely on broad data gathering across a wide spectrum of the enterprise and its environment" (p. 33). Additional research on risk management for complex projects by Williams (2017) found that reactions to risk can

create “causal linkages” (p. 64) between risks, and the project manager and team trying to solve these causal linkages can create “vicious circles of disruption” (p. 62). These linkages and disruption circles can result in project failure, but these linkage risks are rarely seen beforehand.

When evaluating risk and uncertainty, Arashpour et al. (2017) noted the uncertainty in hybrid construction projects must account for on-site and off-site construction-related activities. The authors cited ISO31000 (2009; as cited in Arashpour et al., 2017) and defined uncertainty “as the state of information deficiency related to knowledge of an event, its likelihood, or consequence” (p. 648). The authors referenced PMI’s Project Management Book of Knowledge, or PMBOK (2013; as cited in Arashpour et al., 2017) to note risk is *“*the effect of uncertainty on project objectives” (p. 648).

2.3 Ambiguity & Uncertainty

2.3.1 Ambiguity & Uncertainty Definitions

Like risk, the words *ambiguity* and *uncertainty* can have different definitions attached to them. The PMI (2021) defines uncertainty as “a lack of understanding and awareness of issues, events, paths to follow, or solutions to pursue” (p. 252). The discussion continues by noting uncertainty “is a state of not knowing or unpredictability” (p. 117). Risk, ambiguity, and complexity are all noted to contribute to uncertainty. The PMI (2021) defines ambiguity as *“*a state of being unclear, having difficulty in identifying the cause of events, or having multiple options from which to choose” (p. 235). Ambiguity is broken into two categories, *conceptual* and *situational*. Conceptual ambiguity describes “the lack of effective understanding” (P. 120). This can happen when statements are not

clear and can be interpreted to mean different things. Situational ambiguity is "when more than one outcome is possible" (p. 120). It is noted that methods like progressive elaboration, experiments, and prototypes can help decipher situational ambiguity. In PMI's seventh edition of the PMBOK, the discussion for risk, ambiguity, and uncertainty is included under the *Uncertainty Performance Domain*, which underscores the importance PMI places on these topics.

Hubbard (2020) defined uncertainty *"*as the lack of complete certainty – that is, the existence of more than one possibility. The "true" outcome state, result, value is not known" (p. 112-113). The author continued by describing that the measurement of uncertainty is "a set of probabilities assigned to a set of possibilities" (p. 112-113). The author defined risk as "a state of uncertainty where some of the possibilities involve a loss, injury, catastrophe, or other undesirable outcomes (i.e., something bad could happen)" (p. 112-113). To measure risk, the author recommended using "a set of possibilities with quantified probabilities and quantified losses" (p. 112-113). These risk parameters directly incorporate uncertainty but pertain to negative outcomes only.

Yang et al. (2014) studied overlapping in product development projects and defined uncertainty to describe a condition when the level of overlapping can be defined but the probability distributions related to iteration are unknown. The authors defined ambiguity as a state where the project manager lacks understanding of the process structure and the dependencies between activities. Their paper proposed a quantitative method to describe how uncertainty and ambiguity impact project schedule.

While discussing uncertainty, the term *unforeseeable uncertainties* was introduced (Scrader, Riggs, and Smith, 1993; as cited in Gomes et al., 2019), equated to *unknown-*

unknowns (De Meyer, Loch, and Pich, 2002; as cited in Gomes et al., 2019), and provided another example of the variable terminology used in the field. Gomes et al. (2019) identified *uncertainty blindness* as a challenge and discussed that it can occur if a project manager cannot "define which uncertainties were mitigated" (p. 559) or "why they should invest in reducing the additional ones" (p. 559). The authors proposed *intermediate anchorage* to mitigate uncertainty. Intermediate anchorage is defined as using intermediary artifacts to provide justification for investing in the mitigation of uncertainties for exploratory projects.

Hagen and Park (2013) explored ambiguity acceptance as a critical factor influencing customer and organizational outcomes within the Six Sigma improvement framework. Results indicated a curvilinear relationship between open communication and customer outcomes for team leaders. Multiple regression was used to evaluate open communication and organization outcomes and ambiguity acceptance and customer and organization outcomes for team leaders; positive and significant positive relationships were found, respectively. Hagen and Park (2013) discussed the implications of their research related to the effectiveness of team leaders and noted this is an area of limited research. Regarding the idea that a team leader's ambiguity acceptance can have a positive effect on team outcomes, they noted their research promotes that ambiguity acceptance could be an important project management success factor.

Khodakarami et al. (2007) defined *uniqueness* as having "no similar experience" (p. 39); *variability* as a "trade-off between performance measures like time, cost, and quality" (p. 39); and *ambiguity* as a "lack of clarity, lack of data, lack of structure, and bias in estimates" (p. 39). The paper continues by noting that project scheduling involves

uncertainty since the inputs are not deterministic. The authors proposed an approach using the critical path method and added an explicit uncertainty model incorporating Bayesian networks. The authors used a simple example to conclude that this approach showed promise to improve project scheduling, and they recommended the use of object-oriented Bayesian networks as an approach for real projects.

Lechler et al. (2012) described project risks and uncertainty as *known unknowns* and *unknown unknowns,* respectively. Their research developed categories of opportunities and uncertainties. The authors observed the misperception between risk and uncertainty and between project improvements and opportunities during their research. The authors offered suggestions to better prepare project managers to work through project uncertainty challenges and opportunities.

McLain (2009) worked to further quantify project characteristics' uncertainty through the development of uncertainty terms for: (1) *interdependencies among activities,* (2) *limited information about activity durations,* and (3) *unfamiliarity and variety in project work*. The three uncertainty terms were calculated for two projects and the results discussed. The task-based uncertainty approach and quantification of uncertainty presented by Maes et al., (2022) and McLain (2009), respectively, provide examples of DMDU uncertainty model development.

Ward and Chapman (2003) argued that projects should focus more on uncertainty rather than risk. Reasons for this include: 1) the term risk has become associated with events, and 2) discussions about risk often focus on threats. Focusing more on uncertainty, and less on risk, could provide projects with a more holistic analysis and include exploration in opportunity management. Ambiguity is mentioned by the authors

in a paper section titled “The scope of uncertainty.” The terms of uncertainty and ambiguity have sub-descriptions provided within that section.

Jenson et al. (2006) built a model describing *interactional uncertainty*. The model had two dimensions – *vertical* and *horizontal* uncertainty. Vertical uncertainty referred to vertical relations within an organization (i.e., organization hierarchy); horizontal uncertainty referred to individuals interacting with each other to complete a task. The authors noted that interactional uncertainty is dynamic, and the model analyzed the interplay between vertical and horizontal uncertainty over time. The authors recognized that interactional uncertainty is complemented by operational and institutional uncertainty, and development of strategies for these types of uncertainty, and their interplay with interactional uncertainty, provide good opportunities for future research.

Böhle et al. (2015) argued that uncertainty occurs in technological, organizational, and social contexts. The authors noted that uncertainty occurs in two forms (i.e., *dual uncertainty*): 1) the form of limits to planning due to unexpected events, and 2) the process of coping with these events. This dual uncertainty means that plan-oriented action is insufficient to manage project uncertainty, and experience-based action could yield better uncertainty management. The authors noted that moving to experience-based action is challenging due to the presence of deep-rooted, plan-oriented work processes in many industries, including project management.

Wied et al. (2020) noted that “uncertainty exists when action must be taken without knowledge of the possible outcomes and the probabilities of their occurrence” (p. 75). Projects encountering this are defined as *exploratory*, and this uncertainty paradigm challenges traditional project management. The authors summarize 11 management

approaches for exploratory projects, which they categorize as *preparatory* or pre-action, *attemptive* or during action, and *responsive* or post outcome. The authors recommend shifting focus from *what we know* to *how we act* to manage exploratory projects.

2.3.2 Additional Ambiguity & Uncertainty Literature

Ortiz de Orue et al. (2009) noted that deficiencies exist in project planning tools when addressing project execution uncertainty. They integrated a project organization design simulation tool (Virtual Design Team) with a robust design experimental method to improve project performance. Testing proved this integration possible and showed that it can help project managers design project networks in uncertain environments. Despite enhancing product and project quality in the manufacturing industry, the authors note the slow adoption of robust design methods in other industries.

Gomes et al. (2019) proposed multilevel management of uncertainty when managing exploratory projects. The authors provided a thorough discussion of uncertainty, noted exploratory projects may experience higher uncertainty than incremental development projects, and identified three categories of uncertainty: *primitive*, *structural*, and *elementary*. The authors described that uncertainty management is different than risk management and managing uncertainty should include actions at multiple levels (e.g., *project*, *portfolio*, *organization*, and *network*).

Kvalnes (2016) researched the philosophy of uncertainty in project management and proposed that uncertainty can be an "energizing dimension of projects" (p. 101). This way of thinking about uncertainty removes the negative association and allows project

managers to relate positive outcomes to uncertainty. The author continued by noting that viewing uncertainty holistically requires balancing *welcome* and *unwelcome uncertainty*.

Maes et al. (2022) proposed a task-model approach to integrate uncertainty into project management. The authors developed a task execution strategy based on uncertainty to help project managers select the appropriate task method based on the identified uncertainty. This strategy was validated via four industrial innovation projects. Project teams used four different task strategies, *planning*, *iterating*, *experimenting*, and *executing*, to help them cope with uncertainty. Results indicated that additional uncertainty awareness was achieved, which impacted the project managers' decisions.

Pollack-Johnson and Liberatore (2005) presented an approach to project planning under uncertainty. Their scenario approach analyzed projects with uncertainty in its network structure and/or project durations. It builds on the critical path method by developing a set of network scenarios, each assigned a probability of occurrence. The analysis is flexible and allows for random event consideration, loops, and dependent activity durations. Advantages of the approach include using methods familiar to project managers and implementing them via an array of project management software and tools. The approach helps practitioners better describe project schedule uncertainty compared to more traditionally used methods, and it could be considered an early application of DMDU elements in project management, but the authors do not make this distinction.

Williams and Samset (2010) emphasized decision-making at the beginning of the project's lifecycle. The authors noted that forecasting a project's schedule and cost is difficult for major projects. This is compounded by an overestimation of project benefits.

Since many projects rely on a benefit/cost ratio to measure success, underestimating costs and overestimating benefits skews the ratio towards project completion.

Along with acknowledging a lack of accurate information early in the project, the authors described the situation of *analysis paralysis* (Samset, 2009 as cited in Williams and Samset, 2010), which occurs when too much information is presented to a project team too early. In addition, project quantitative information can become outdated quickly. The article referenced this as *half-life of information*. The authors concluded by discussing additional research topics and noted that the research could yield information that helps project managers make front-end decisions that produce wanted projects.

Saunders et al. (2015 and 2016) noted the importance of managing uncertainty in safety-critical projects where failure consequences can be serious. They developed an *uncertainty kaleidoscope* to understand its sources. The kaleidoscope was developed and validated over the two papers, and it represents an approach to uncertainty modeling. The authors discussed that the kaleidoscope could help project managers identify sources and influences of uncertainty and improve project management implementation.

Arashpour et al. (2016) analyzed project uncertainty in hybrid construction projects and proposed a holistic risk analysis approach to assess the integration of uncertainties on project completion times. If project managers integrate the evaluation of on-site and off-site uncertainties, and senior executives provide resource support to on-site and off-site activities, it may be possible to reduce the risk of schedule overruns and resultant late completions in the hybrid construction industry. This differs from the current practice of project managers separately analyzing uncertainties for on-site and off-site activities.

Walker et al. (2017) evaluated managing uncertainty and ambiguity through team collaboration during infrastructure projects. Their analysis included background definitions and discussions on risk, uncertainty, and ambiguity. The authors developed a *sense-making approach* (Walker et al., 2017 as cited in Weick, 2001 and Weick et al., 2005) and used the *Cynefin* ambiguity framework (Walker et al., 2017 as cited in Kurtz and Snowden, 2003). Results indicated that collaboration could lead to a decrease in people and process ambiguities, and observing previously unrecognized ambiguity can assist coping strategies.

Gomes et al. (2021) discussed uncertainty propagation in open innovation projects. Uncertainty propagation describes the diffusion of uncertainty throughout an inter-organizational project. The authors noted that project managers, or the firms they represent, rarely have complete information on project attributes like scope and budget. The authors recognized this and presented two implications; 1) managers could set rules for information sharing and uncertainty propagation occurrence, and 2) contracts should account for roles and responsibilities to assess and respond to uncertainty propagation. The authors discussed the lack of theoretical understanding on how project managers work through the development and diffusion of uncertainty in open innovation projects.

Wiewiora and O'Connor (2022) provided a discussion on the definition of ambiguity and discussed research to determine the types of project ambiguity that project managers experience and how it is managed. The two highlighted studies resulted in additional ambiguity knowledge that included development of seven higher order categories; the discovery that *task related* ambiguities and *people related* ambiguities resulted in more positive and negative emotions, respectively; and that experienced project managers have

a range of practices to manage ambiguity. The authors noted that better understanding of ambiguity could help support and training methods for project managers.

2.4 Decision-Making Under Deep Uncertainty

2.4.1 DMDU Types of Uncertainty

Many projects, including in engineering management, face deep uncertainty at their onset; therefore, DMDU techniques may improve uncertainty management in projects. This section will provide background on DMDU applicability and its techniques. In addition, DMDU implementation examples will be reviewed to show the application of these techniques in different disciplines.

Marchau et al. (2019) discussed the challenges that practitioners face when attempting to account for future decision-making uncertainty. They separated uncertainty into four levels; Table 2.1 provides comparative summaries of the levels. *Level 1 uncertainty* occurs when one does not see a need or cannot measure the uncertainty. These cases are often short-term decisions with a well-defined system. A simple model and sensitivity analysis can be used for analysis.

Level 2 uncertainty can be described using a probabilistic model or with futures that have probabilities assigned (i.e., Level 2 uncertainties can be solved using the methods of probability and statistics). Model outcomes evaluated against expected outcomes and acceptable risk can be used to make decisions. *Level 3 uncertainty* cannot be evaluated using probabilities, but scenarios can describe the system well enough to make decisions. The scenarios are evaluated using the best available information to examine

consequences and determine the most favorable result. Marchau et al. (2019) described an umbrella in your car in case of rain as an example of Level 3 uncertainty.

Level 4 uncertainty is characterized as the *black swan* event. It is the most extreme case of measurable uncertainty and has two sub-conditions: 1) *Level 4a* represents a case where there is difficulty specifying models, interactions, probabilities, and/or the value proposition of scenario outcomes, and 2) *Level 4b* represents a case where an analyst cannot specify the items listed under Level 4a. The definitions, *complete determinism* and *total ignorance*, represent knowing everything and not knowing anything, respectively.

Table 2.1. Descriptions of levels of uncertainty (adapted from Marchau et al. (2019).

	Level 1	**Level 2**	**Level 3**	**Level 4**
Description	Short-term decision for a well-defined system	Situation can be defined using probabilities	Probabilities cannot describe decision; defined using scenarios	Broken into two categories: bounded with possible futures (4a) and know future is unknown (4b)
Analysis Method	A simple decision model coupled with sensitivity analysis	A model using probability and statistical analysis	A model using a scenario analysis approach	Difficult to describe model parameters under 4a; cannot describe parameters under 4b

***Levels of uncertainty are bounded by complete determinism (fully understood system) and total ignorance (do not understand system).**

Marchau et al. (2019) noted that an uncertainty level evaluation is important since DMDU methods have costs and benefits. As one approaches Level 4 uncertainty, analytic approaches like DMDU are appropriate since the level 1 through 3 evaluation methods perform inadequately (i.e., DMDU methods can be most effective in this space).

2.4.2 DMDU Methodology

Marchau et al. (2019) provided the following steps for DMDU: *frame the analysis, perform exploratory uncertainty analysis, choose initial actions and contingent actions,* and *iterate and re-examine*. The authors continued to describe early DMDU approaches by discussing *Assumption Based Planning*, which includes *Exploratory Modeling* and *Scenario Discovery*, and they discussed that Assumption Based Planning was the beginning of an evolution towards the five DMDU approaches presented in the book, which were *Robust Decision[-M]aking*, *Dynamic Adaptive Planning*, *Dynamic Adaptive Policy Pathways*, *Info-Gap Decision Theory*, and *Engineering Options Analysis*.

The five methods described by Marchau et al. (2019) are further described here. First, Robust Decision-Making (RDM) creates better decisions, rather than better predictions, when facing deep uncertainty. The RDM process uses stress tests and analytics to identify strategies that are relevant and adaptive. Second, Dynamic Adaptive Planning defines an initial plan while uncertainties exist and adapts the plan over time as knowledge is gained. A monitoring program is developed, and responses trigger at predetermined threshold values. Third, Dynamic Adaptive Policy Pathways (DAPP) evaluates action timing and develops alternatives for the future. If *Adaptation Tipping Points* are reached, an alternative route is selected. Fourth, Info-Gap Decision Theory evaluates known and unknown information to determine a *reliable and responsible decision*. The method

works to optimize *robustness to failure* for deep uncertainty conditions. Fifth, Engineering Options Analysis uses a process to assign economic value to technical feasibility through calculations of the value of provided flexibility.

2.4.3 DMDU Applications

Cox (2012) provided an overview of DMDU techniques and noted the applicability to deep uncertainty problems in many industries including climate change, epidemics, species protection, financial systems, power grid design, and cybersecurity. Cox (2012) continued by discussing how risk analysts could use methods for risk analysis under deep uncertainty to improve decision-making. The discussion highlighted a strength of the DMDU techniques, which is the flexibility to analyze problems from multiple topic areas. Aven (2013) continued the discussion of deep uncertainties in risk analysis. The author noted that there are many ways to evaluate robustness, and there may not be an argument for why one way is better than another; therefore, they call for managers to review the robustness analysis and use the outcomes for decision-support.

Ben-Haim and Laufer (1998) developed the robust reliability concept (i.e., Info-Gap Theory) and applied it to improve project management performance metrics related to the reliability and duration of project scheduling. The authors defined uncertainty as *structured* and *unstructured*. Structured uncertainty can be described with a probability density function; unstructured uncertainty is unexpected, and it is less likely that sufficient data to build probability density functions are available. The developed solution included four characteristics: *minimal information*, *subjective information*, *simplicity*, and *enhancement and assessment of reliability*.

Hall et al. (2012) researched the performance of RDM and the Info-Gap method to evaluate alternatives for climate change scenarios where significant uncertainties exist. The authors discussed how both rely on multiple futures development and work to identify robust strategies. The two methods have notable differences, including how they handle imprecise probabilistic information. The author's analysis showed that the two approaches reached similar, but not the same, conclusions regarding policy recommendations, and this creates questions about each method and their role for decision-support.

Kwakkel et al. (2016) discussed the application of RDM and DAPP to *wicked* policy problems. The authors described that RDM requires upfront work to scope the problem and system boundary and agree on outcomes. This requires stakeholder engagement and agreement early in the process. Another challenge of using RDM in this context is that many policy-related decisions are irreversible with path dependency. The RDM analysis, through stress testing, can reduce the number of scenarios where failure occurs; however, it lacks detail on the adaptation of plans over time and struggles with support for path dependency. The authors recommended that RDM and DAPP address different parts of wicked problems; therefore, combining elements of RDM and DAPP may generate positive momentum towards using DMDU methods on wicked policy problems.

Kwakkel et al. (2016) compared RDM and DAPP to a hypothetical technical problem based on the Waal, which is a river reach in the Netherlands. The case study evaluated floodplain management strategies and included future uncertainties of climate change and socio-economic development. The authors concluded that RDM and DAPP can design strategies when deep uncertainties exist. As with wicked policy problems (Kwakkel et al.,

2016), the authors promoted combining RDM and DAPP, and noted more research could evaluate commonalities among RDM, DAPP, and other DMDU methods.

Tahan and Ben-Asher (2005) studied the performance of Info-Gap Theory to evaluate the system integration process. Single-stage and incremental integration were evaluated by both a Generalized Activity Network and an Info-Gap model. The authors noted that the activity network relies on previous knowledge and probability density functions, while the Info-Gap model does not and provides information on how close measures are to failure compared to pre-defined requirements.

Results from the Tahan and Ben-Asher (2005) analysis yielded that the incremental system integration method was preferrable for complex systems. From a statistical perspective, the two integration approaches performed similarly for simple systems, and this conclusion was consistent for different probability distributions. For simple systems, the Info-Gap model found incremental integration performed better in terms of robustness. The authors concluded that incremental integration is recommended under severe uncertainty where basic probability metrics cannot be estimated, with this recommendation also applying to simple systems. If the simple system has predictable integration processes, one could consider the single-stage option.

Other DMDU research examples include studying decision-making based on evidence and the impact true evidence can have on uncertainty knowledge (Ben-Haim, 2024). Groves et al. (2014) summarized a case study by the Metropolitan Water District of Southern California and their RDM approach to water planning. Reis and Shortridge (2020) evaluated a reservoir system in Ethiopia as an RDM case study for climate change adaptation. The authors suggested that RDM should use *extended, uniform parameters*

distributions. Lempert and Turner (2021) used RDM to evaluate three worldviews using the *lake problem*. Each worldview was evaluated separately by RDM, and the results provided information about how the analysis could be used to facilitate stakeholder engagements between groups having different worldviews.

2.5 Statistical Applications

Clark (1962) clarified the application of the PERT methodology. The author summarized the methodology's development and described the justification for collecting most likely (i.e., mode) and extreme (i.e., optimistic and pessimistic) activity time estimates and selecting the Beta distribution. The author continued by describing how to convert the three-point estimate into an expected value and variance.

Van Slyke (1963) evaluated the PERT and Monte Carlo methodologies on a network example and compared the results. Their analysis continued by testing the feasibility of Monte Carlo simulation and developing shortcuts to reduce computational time. The PERT method relies on development of a critical path (i.e., longest path), but project managers must understand that the critical path is uncertain. The author discusses how Monte Carlo simulation provides *criticality index* information that can identify the likelihood of arcs between activities being critical.

Min and Shou-rong (2013) used a dynamic triangular distribution to represent activity uncertainty and a Monte Carlo simulation to model total project duration. The activity distribution parameters were changed, and the magnitude of the changes in project durations were evaluated. The authors observed that student syndrome (i.e., procrastination) and Parkinson's Law (i.e., the work will use the available time)

influenced project duration in positive or negative directions, depending on the distribution changes. The authors discussed the shortcomings of project duration estimates and how the Critical Chain method helps by relying on minimum activity duration estimates and no reserves.

Deshmukh and Rajhans (2018) compared PERT to Monte Carlo simulation through a hypothesis test (i.e., paired t-test) using a manufacturing industry project example. The authors discovered a significant difference between the results of the two methods, with Monte Carlo analysis results closer to "practical project completion duration" (p. 12). The authors concluded project managers can evaluate schedule risk using Monto Carlo simulation and the resultant criticality index and project completion probabilities.

Cho and Yum (2004) proposed a method for estimating the criticality index and the sensitivity analysis of expected project completion time with respect to expected activity duration. The analysis used a Taguchi orthogonal array experiment to estimate the criticality index as a function of expected activity duration. The method accuracy was tested using sample PERT networks and it was compared to a Monto Carlo simulation. The author noted that the orthogonal array experiment is computationally more efficient than Monte Carlo simulation. Bowman (2007) developed an alternative methodology and reported more accurate estimates than Cho and Yum's (2004) with fewer simulations.

2.6 Engineering Management

The growth of research in the new product development process over the past 30 years (Marzi et al., 2021) was observed in Chapter 1 (Introduction). Additionally, an example from Lévárdy and Browning (2009) was discussed to highlight the impact

uncertainty can have on project success. This engineering management literature review will provide additional context, introduce project uncertainty management methods, and discuss their ability to reduce project uncertainty and/or improve project performance metrics.

2.6.1 Engineering Management Uncertainty Applications

To help with the project uncertainty problem, previously cited Lévárdy and Browning (2009) developed an adaptive product development process that linked project decision-making to maximizing the expected overall project value. This was accomplished through thousands of simulations of adaptive cases to determine the process (i.e., path) with the highest value. The analysis evaluated costs, duration, risks, and other metrics. Evaluating a product development path as a process space with options provided a new way of thinking about how to complete a product development project.

Assaad et al. (2020) observed, and it was reported in Chapter 1 (Introduction), that cost and schedule overruns affect construction industry projects. The authors commented that the successful execution of construction projects could be enhanced by tools that identify cost and schedule overrun problems early in the project lifecycle. The authors proposed an evaluation framework to quantify risk by cost and schedule, created an assessment model, and used the system to predict the project cost and schedule at completion. The developed model was demonstrated using a hypothetical dataset, and the authors noted “the proposed model reflected its practicality and reliability in predicting project performance” (p. 04020030-18).

Schrader et al. (1993) discussed three key points about uncertainty and ambiguity. First, they noted that the terms represent two separate concepts. The authors framed uncertainty as not knowing the outcome, and ambiguity as not being satisfied with the understanding of the problem structure. The authors also broke ambiguity into two levels. Second, the authors summarized that uncertainty and ambiguity are not determined by external factors, but rather they are determined when the problem is framed. Third, the authors discussed the determination of uncertainty and ambiguity and the resultant impact on the problem solution. A framework (i.e., matrix) to evaluate both uncertainty and ambiguity reduction is proposed and explained.

De Meyer et al. (2002) discussed project uncertainty and its global impact on the project management community. The authors defined four types of uncertainty: *variation, foreseen uncertainty, unforeseen uncertainty*, and *chaos,* and they studied uncertainty in 16 projects representing multiple industries including technology, mining, pharmaceutical, and construction. The authors noted that a failure to recognize the type(s) of uncertainty affecting a project, and the associated management approach, were key contributors affecting project success. They argued that an uncertainty management approach informed by the four types of uncertainty could improve project performance.

Qazi et al. (2020) noted that uncertainty can lead to negative or positive events, and they presented a new term called *uncertainty thinking*. A Bayesian Belief Network and Influence Diagram were implemented for uncertainty evaluation. The illustrative example's results displayed the importance of risk and opportunity modeling on uncertainty evaluations. A hyperfocus on negative uncertainties, or risks, can result in a

sub-optimal decision-making process. The authors observed that minimizing a risk's expected loss may not maximize the expected gain when evaluating a risk network.

Sjödin et al. (2016) researched uncertainty and equivocality in process development. The authors used data from 251 responses representing 52 joint process development projects to build a framework based on *early end user involvement* and *joint problem solving* to reduce uncertainty and equivocality. The study evaluation indicated that uncertainty has negative consequences for project budgets, the early involvement of end-users reduces uncertainty, and joint problem solving reduces equivocality. The authors noted their data were limited to four Swedish process firms and their equipment suppliers and generalizations regarding a larger population were outside the study scope.

Chang and Chiu (2005) studied the uncertainty and equivocality in engineering consulting projects. A survey of 108 project managers provided data to analyze and evaluate against company metrics like productivity. The recommendations included that engineering design work could benefit from additional data acquisition and analysis and less problem definition and interpretation. Moreover, project nature (i.e., simple or complex) does not affect productivity and profitability, and planning projects have higher levels of ambiguity compared to design work. It was observed that projects with larger contracted amounts have higher levels of uncertainty and ambiguity, but long duration projects don't exhibit the same pattern.

Hoffman et al. (2007) analyzed data from 856 facility projects completed between 1988 and 2004 with two methods: 1) Bromilow's time-cost model, and 2) multiple linear regression. The multiple linear regression model provided the best prediction, and the regression model found the correlation between project duration and cost to be

significant. Like Assaad et al. (2020), this research demonstrates the importance of project duration and cost and shows that reducing uncertainty to those metrics could yield positive benefits.

Zheng et al. (2019) evaluated behavioral relationships and their effect on megaprojects. The authors examined three governance areas: *contract*, *trust*, and *institutional support* through data collection with 202 contractors and consultants in China affiliated with megaprojects. Project uncertainty was found to moderate relationships between both *trust* and *relational behavior* and *contractual contingency adaptability* and *relational behavior*. That said, it negatively influenced the relationship between *contractual term specificity* and *relational behavior*. Evaluating a megaproject's uncertainty and how the three key paths (i.e., contract, trust, and institutional support) affect relational behavior can help managers understand project governance and improve relationship management in the project.

2.6.2 Fuzzy Model Applications in Engineering Management

Shipley et al. (1997) compared the calculated activity times of fuzzy probability estimations and the Beta distribution as part of a PERT analysis. The fuzzy probability estimations differ from Beta distribution parameters because the accuracy of the time estimates (i.e., pessimistic, most likely, optimistic) are evaluated by the project manager prior to critical path calculation at the beginning of the project. The paper describes that time estimates are evaluated as part of a PERT analysis, but many times the amount of schedule padding that an activity manager adds is not evaluated until the end of the process, which can result in avoidable cost increases.

Zhong et al. (2018) developed a fuzzy mathematics framework to evaluate uncertainty impact against project performance. Model results indicated that uncertainty adjusts project parameters, which results in changing performance. The sources of uncertainty determine the uncertainty-changing mechanisms. The authors discussed that the findings from this research are applicable to the project management community at-large, but they noted that the presented research focused on a single construction project.

2.6.3 Statistical Applications in Engineering Management

Sadeghi et al. (2024) studied how sample size affects probability distribution selection for activity durations. The selection of an activity duration distribution for large sample sizes is less challenging than when selecting a distribution for small sample sizes. Using Monte Carlo simulation to estimate the project duration distribution, the authors evaluated the synthesis of 3,264 stochastic project networks. The activity distributions were varied, and the impact of these changes on the overall project duration distribution was examined. The authors concluded that sample size influences activity distribution selection and recommended using the normal distribution for sample sizes below 50.

Salas-Morera et al. (2018) challenged the assumption that the normal distribution is appropriate to describe the probability function of total project time for complex projects. The authors developed a methodology to evaluate different distributions and proposed the Gamma distribution as an alternative. Their results indicate that the Gamma distribution is suitable for use in most cases, and this is especially true when the Beta distribution is used to model the underlying activities. The authors noted these findings could improve project performance without substantially changing the methodology or tools used.

2.6.4 Additional Engineering Management Literature

Cates and Mollaghasemi (2007) discussed the Project Assessment by Simulation Technique. The technique interconnects *managerial controls, modeling, input analysis, and output analysis* and facilitates the sharing of information with project stakeholders. The authors stressed that developing project simulations and distribution functions at the beginning of a project is an important step that can inform decision-making by providing a deeper appreciation of risks and opportunities. Continuing to revisit the model and outputs as the project moves forward can provide information about where intervention is needed and maintain positive momentum.

Kolltveit et al. (2004) researched taking advantage of opportunities in the early project phases. Their paper noted that the terms risk and uncertainty are often interchanged. Furthermore, the authors discussed the confusion surrounding the definition of risk, and that many risk practitioners tend to focus on the negative effects. This leads to missing the identification of opportunities that could benefit the project. Regarding the term uncertainty, the authors noted it includes both opportunities and risks, and they discussed *internal* and *external* sources of uncertainty. An evaluation of four projects displayed that a project's uncertainty profile, and resultant profit potential, are affected by project strategy.

Browning and Eppinger (2002) explored schedule risk as part of product development through development of a model of activities that exchange deliverables. Simulations were performed with cost and schedule distribution outputs. It was noted that process architecture input variations altered the model output distributions. Comparing different input process architectures revealed cost and schedule risk tradeoff opportunities.

Zhang et al. (2024) developed a decision model to evaluate risk to a portfolio of projects. The model was "a four-stage interval optimization model based on a two-tier risk-project network" (p. 7364). Validation of the model was conducted by evaluating risk response decisions made by a Chinese construction firm. The authors noted that the proposed model provided the managers with a process-based guide to help them make risk response decisions for single projects within project portfolios.

Petronijevic et al. (2023) studied risk attitudes in engineering. The paper provides important observations related to risk management. First, risk is a support activity that doesn't exist on its own. Second, analyzing risk and associated engineering processes separately can lead to a lack of engineering view, and while both views have utility, there is a middle space requiring additional work to manage risk. Third, how risk is treated can result in different definitions, and risk management in engineering fields has developed methodologies that create additional definitions. Fourth, future work to develop risk management tools with a global risk notion could help address inconsistencies.

An evaluation of the Critical Chain method and comparison to the Critical Path method was completed by Lechler et al. (2005). The methodology differences include how each treats safety margin, and in the case of Critical Chain, the use of Theory of Constraints. This difference in how project uncertainty is treated can result in difference baseline schedules being developed by each method. The authors observed that the Critical Path method is widely accepted, and so knowing how the Critical Chain method will contribute to project management is unknown. Related to implementation, four Theory of Constraints practices have been identified that can be implemented without the entire Critical Chain methodology. The practices include managing constraint resources

to help resource conflicts, reducing work-in-process and multitasking, and focusing and prioritizing projects on systems throughput versus individual specific projects.

Pulat and Horn (1996) described the *time-resource tradeoff problem* and presented a multiple objective linear programming model. Assuming a project network precedence diagram, the time-resource tradeoff problem determines project schedules that are efficient for a range of project completion times. Enumerative and interactive algorithms were described as solutions and the computation times compared. It was reported that both versions had acceptable computation times.

Mokhtari et al. (2011) evaluated the time-cost tradeoff problem to improve the project completion probability while expending a limited budget. A discrete time-cost tradeoff problem was evaluated with four extreme strategies related to the mean and variance of normally distributed activities. An *Ant Colony System algorithm* allocated the activity budget, and a solution by LINGO optimization software was used to benchmark. Comparison results showed good performance for the Ant Colony System algorithm.

The establishment and growth of the project management industry were observed by Grant and Pennypacker (2006). The authors evaluated whether this growth was occurring consistently across four industries: *professional, scientific and technical services; information; finance and insurance; and manufacturing*. Their research determined that there were not significant differences in project management maturity between industries, and it provided a baseline evaluation of maturity for the project management community.

Xue et al. (2022) proposed an operational framework to align standards and integrate business practices. A key idea behind the framework was improving coordination

between project managers and system engineers. Important standards for each community were reviewed and a recommendation to align some processes was provided. To enhance the coordination beyond standards management, the authors recommended an adjustment in mind-set and noted that project managers and system engineers need to work together, improve focus, and eliminate dueling visions. While this type of work is different than the direct management of projects, decisions related to business practices can help, or hinder, the ambiguity and uncertainty related to business practices.

2.7 Summary and Conclusions

Sections 2.2 and 2.3 discuss how risk, ambiguity, and uncertainty are defined in literature, respectively. The sections also discussed the interplay between risk and uncertainty, and how an industry standard definition of risk has been elusive. Previous applications for improving project management methods to better account for risk, ambiguity, and uncertainty were described. Using this information, the praxis definitions of risk, ambiguity, and uncertainty are below, with appropriate citations.

Ambiguity: Not knowing what you don't know (Lévárdy and Browning, 2009).

Opportunity: An event that, if it occurs, will have a positive effect on the project. Opportunity can be represented through probability of occurrence and consequence. The opposite of opportunity is risk (adapted from PMI, 2021; Kaplan and Garrick, 1981).

Risk: An event that, if it occurs, will have a negative effect on the project. Risk can be represented through probability of occurrence and consequence. The opposite of risk is opportunity (adapted from PMI, 2021; Kaplan and Garrick, 1981).

Uncertainty: Knowing what you don't know (Lévárdy and Browning, 2009). Uncertainty includes both opportunities and risks (Kolltveit et al., 2004).

Elements of the PMI (2021) and Lévárdy and Browning (2009) definitions of risk were used in the praxis definition. A difference from the PMI (2021) definition is that risk represents only negative events. This removes the need to define *threats* but creates a need to define opportunities. The praxis definitions for risk and opportunity recognize that both can be represented through probabilities of occurrence and consequence. Given that risks and opportunities are event-driven, the totality of project risk and opportunity is considered *Total Project Uncertainty*. This is like PMI's (2021) definition of *Overall Project Risk*. The praxis definition of ambiguity, from Lévárdy and Browning (2009), represents unknowns, and ambiguity is treated as separate from uncertainty.

Section 2.4 defined DMDU, discussed DMDU methodologies, and provided case studies from other disciplines. Sections 2.5 and 2.6 reviewed example statistical applications and how the engineering management profession has improved its understanding of risk, ambiguity, and uncertainty, respectively.

Chapter 3: Methodology

3.1 Introduction

This praxis chapter is organized into seven sections, excluding the introduction. Each of the first six sections represents a step in the proposed methodology (i.e., framework). The framework steps include Project Diagramming, Model Statistical Uncertainty, Model Deterministic Uncertainty, Model Risk & Opportunity, Risk & Opportunity Recommendations, and Monitor & Compare. Figure 3.1 provides an overview of the framework. The final section provides a framework summary.

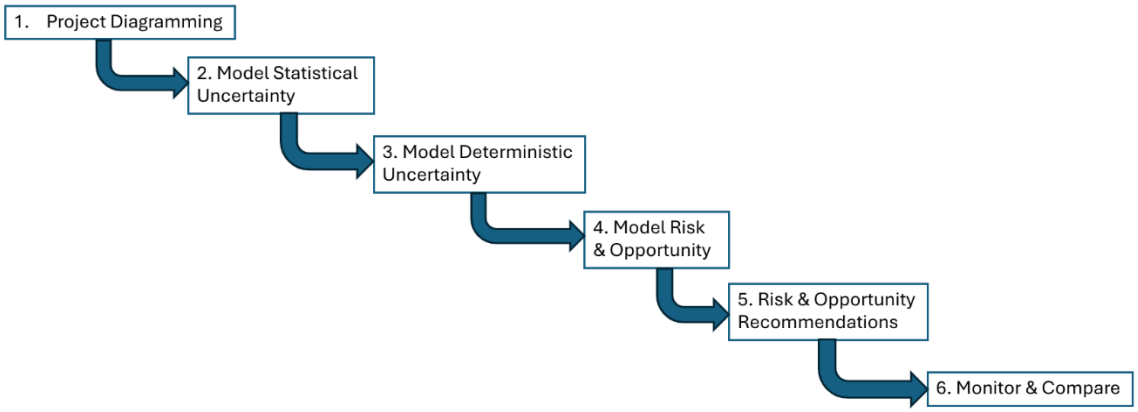

Figure 3.1. The uncertainty evaluation and risk recommendations framework steps.

Several principles are foundational to the development of the framework outlined in this chapter. First, the framework is responsive to the praxis problem statement; thesis statement; and research objectives, questions and hypotheses. Second, the framework represents a holistic approach to the evaluation of project uncertainty and development of event-driven risk recommendations. Third, the framework is flexible regarding evaluation tools and statistical methods selection (i.e., the user can select tools and methods they prefer and fit them to the framework steps). This praxis implements example statistical

applications in Microsoft Excel to provide a proof-of-concept computational tool. Fourth, the framework focuses on industry-standard practices to give implementation flexibility. Fifth, the recommendation is to carry out the framework at the beginning of a project with iterations of required steps, as needed.

3.2 Project Diagramming

The first framework step is *Project Diagramming,* and the first sub-step is building a network diagram to represent the project steps. These diagrams have different forms, such as activity-on-arrow and activity-on-node. Activity-on-arrow diagrams use arrows to represent activities and nodes to represent transitions. Activity-on-node diagrams use nodes to represent activities and arrows to represent transitions (Pinto, 2020). Figure 3.2 is an example activity-on-node diagram. The activity-on-arrow diagram used for the praxis evaluation is shown in Chapter 4 (Results).

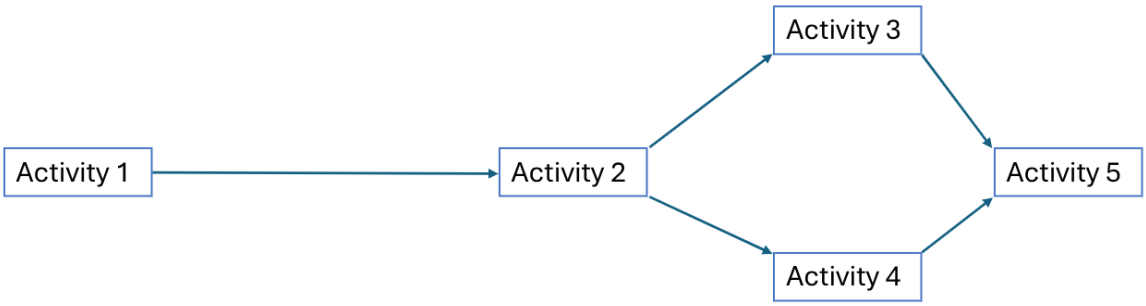

Figure 3.2. An example activity-on-node network diagram.

The second sub-step is activity duration estimation. Several methodologies are available to estimate initial activity durations (e.g., analogous, parametric, single-point estimates) (Project Management Institute (PMI), 2021), and subject matter experts may help with their development. The praxis methodology does not prescribe a method to determine the activity durations, but the eventual requirement is a three-point (i.e.,

optimistic, most likely, and pessimistic) duration estimate for each activity. At the start of the project, if only most likely activity duration estimates are available, PMI (2021) recommends –25% and +75% of this value for the optimistic and pessimistic estimates, respectively. The range is reduced to –5% and +10% for the optimistic and pessimistic estimates, respectively, for projects that are far along in their life cycle (PMI, 2021). Table 3.1, columns D, E, and F provide an example of optimistic, most likely, and pessimistic duration estimates.

3.3 Model Statistical Uncertainty

The second framework step is *Model Statistical Uncertainty,* and the first sub-step is calculating activity and project expected values, standard deviations, and variances, and the project's critical path. Equation 1 – Activity Expected Val. and Equation 2 – Activity Std. Dev. from the Program Evaluation and Review Technique (PERT) are used to calculate activity expected value and standard deviation, respectively (Clark, 1962). The PERT methodology applies a Beta distribution to project activity times. Table 3.1, columns G and I provide an example of the activity expected values and standard deviations, respectively.

$$Activity\ Exp.\ Val. = \frac{[Optimistic + (4 \cdot (Most\ Likely)) + Pessimistic]}{6} \quad (1)$$

where:

Activity Exp. Val. = The activity duration expected value [Time]

Optimistic = The optimistic activity duration estimate [Time]

Most Likely = The most likely activity duration estimate [Time]

Pessimistic = The pessimistic activity duration estimate [Time]

$$Activity\ Std.\ Dev. = \frac{Pessimistic - Optimistic}{6} \quad (2)$$

where:

Activity Std. Dev. = The activity standard deviation [Time]

Pessimistic = The pessimistic activity duration estimate [Time]

Optimistic = The optimistic activity duration estimate [Time]

The critical path is the longest duration completion path for a project, which is the fastest duration a project can be completed (PMI, 2021). A critical path delay results in a project delay. Using figure 3.2 as an example, the paths of *Activity 1 – Activity 2 – Activity 3 – Activity 5* and *Activity 1 – Activity 2 – Activity 4 – Activity 5* durations would be summed, and the largest duration assigned to the critical path. The praxis framework uses activity expected values from equation 1 to determine the critical path.

Microsoft Excel's Solver calculated the critical path by maximizing objective cell G*18* in table 3.1. To do this, the formula *=SUMPRODUCT($G$2:$G$17, $M$2:$M$17)* was entered into cell *G18* to calculate the total project expected value and the Solver objective cell (i.e., the cell Solver calculates) was set to *$G$18* with the *Max* option selected. Next, the constraints were identified as a flow problem by entering the formula *=SUMIF($B$2:$B$17, P2, $M$2:$M$17) - SUMIF($C$2:$C$17, P2, $M$2:$M$17)* in column Q and entering *$Q$2:$Q$12=$S$2:$S:$12* into Solver, the *Make Unconstrainted Variables Non-Negative* was checked, and the solving method set to *Simplex LP*. Finally, Solver identified the critical path activities with a *1* and activities not on the critical path with a *0* in column M and the resultant project expected value duration (i.e., the longest flow path) was calculated in cell *G18*. Figure 3.3 shows the Solver parameters.

Table 3.1. Table showing Microsoft Excel cells used in statistical analysis.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Activity	From	To	Optimistic Estimate	Most Likely Estimate	Pessimistic Estimate	PERT Expected Value	PERT Variance	PERT Std Dev	Triangular Expected Value	Triangular Variance	Triangular Std Dev	Critical Path (1=Yes, 0=No)	Monte Carlo Duration		Nodes	Net Flow		Supply/ Demand
2	STARTto1	START	1	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00		START	1	=	1
3	1to2	1	2	6	12	30	14.00	16.00	4.00	16.00	26.00	5.10	1	11.14		1	0	=	0
4	1to3	1	3	8	10	20	11.33	4.00	2.00	12.67	6.89	2.62	0	13.87		2	0	=	0
5	2to6	2	6	6	11	40	15.00	32.11	5.67	19.00	56.17	7.49	0	37.15		3	0	=	0
6	2to4	2	4	3	21	40	21.17	38.03	6.17	21.33	57.06	7.55	1	25.66		4	0	=	0
7	3to4	3	4	12	15	20	15.33	1.78	1.33	15.67	2.72	1.65	0	18.35		5	0	=	0
8	3to5	3	5	8	17	21	16.17	4.69	2.17	15.33	7.39	2.72	0	12.85		6	0	=	0
9	4to7	4	7	6	12	25	13.17	10.03	3.17	14.33	15.72	3.97	0	14.42		7	0	=	0
10	4to5	4	5	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00		8	0	=	0
11	5to7	5	7	7	14	21	14.00	5.44	2.33	14.00	8.17	2.86	0	17.30		9	0	=	0
12	5to9	5	9	25	30	40	30.83	6.25	2.50	31.67	9.72	3.12	1	28.55		END	-1	=	-1
13	6to8	6	8	1	1	1	1.00	0.00	0.00	1.00	0.00	0.00	0	1.00					
14	6to7	6	7	3	12	18	11.50	6.25	2.50	11.00	9.50	3.08	0	16.46		Monte Carlo Expected Value			
15	7to9	7	9	7	9	12	9.17	0.69	0.83	9.33	1.06	1.03	0	7.97		68.86			
16	8to9	8	9	6	9	11	8.83	0.69	0.83	8.67	1.06	1.03	0	8.59					
17	9toEND	9	END	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00		Monte Carlo Std Dev			
18	TOTAL			34.00	63.00	110.00	66.00	60.28	7.76	69.00	92.78	9.63		65.34		9.69			

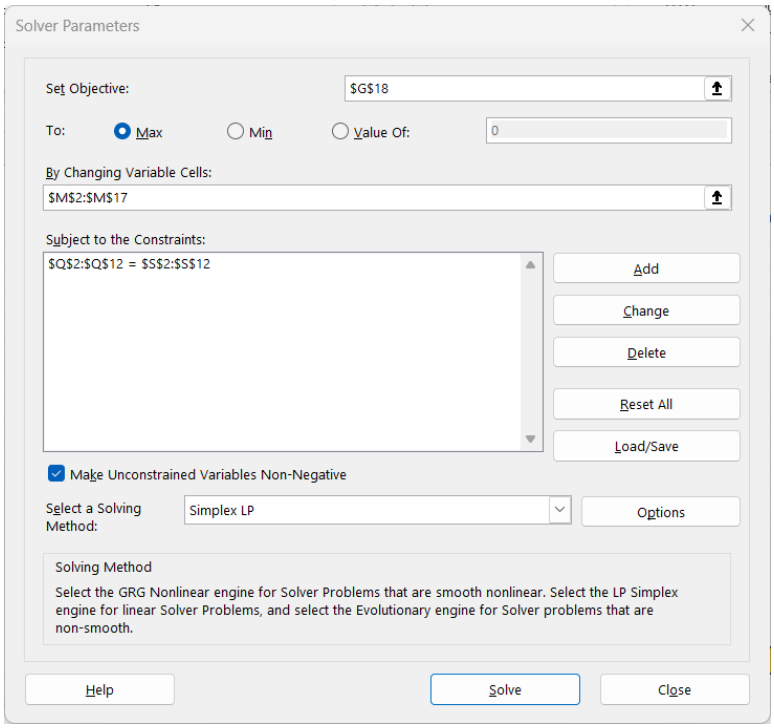

Figure 3.3. Microsoft Excel Solver parameters from table 3.1.

Table 3.1, column H provides example variance calculations using Equation 3 – Activity Variance and calculating total project variance in table 3.1, cell *H18* using the Excel formula *=SUMPRODUCT($H$2:$H$17,$M$2:$M$17)*. Equation 4 – Total Project Std. Dev. calculates the total project standard deviation in table 3.1, cell *I18* from the total project variance.

$$Activity\ Variance\ =\ (Activity\ Std.\ Dev.)^2 \quad (3)$$

where:

Activity Variance = The activity variance [Time^2]

Activity Std. Dev. = The activity standard deviation [Time]

$$Total\ \text{Pr}oject\ Std.\ Dev.\ =\ \sqrt{(Total\ \text{Pr}oject\ Variance)} \quad (4)$$

where:

Total Project Std. Dev. = The total project standard deviation [Time]

Total Project Variance = The total project variance [Time^2]

The second sub-step is developing a Normal distribution using the total project expected value and standard deviation. The Microsoft Excel function *NORM.DIST(value, mean or expected value, standard deviation, cumulative distribution function (TRUE) or probability density function (FALSE))* calculates both cumulative distribution and probability density functions. The Normal distribution representation for total project duration is an assumption of the PERT methodology, and that assumption means activity times are considered statistically independent (Pinto, 2020). Microsoft Excel requires expected value and standard deviation for Normal distribution calculations, but other tools may use expected value and variance.

A Triangular distribution based on the same critical path as the PERT methodology provides an alternative statistical method (i.e., a practitioner can select either or both options). The Triangular distribution is a good comparison distribution candidate because it also uses three-point activity duration estimation (Sadeghi et al., 2024). An example of the activity calculations for the Triangular distribution expected value, variance, and standard deviation are found in table 3.1, columns J, K, and L, respectively, and

Triangular distribution formulas for expected value and variance are represented by Equation 5 – E(X) and Equation 6 – Var(X), respectively (Garvey et al., 2016). Equation 3 calculates the activity standard deviation using the known variance. The activity-level expected values, variances, and standard deviations can be combined to develop total project metrics using the described PERT methodology, and a Normal distribution can model total project duration. Table 3.1, cells *J18*, *K18*, and *L18* provide an example of the total project expected value, variance, and standard deviation, respectively.

$$E(X) = \frac{(a + m + b)}{3} \tag{5}$$

where:

E(X) = The Triangular distribution expected value [Time]

a = The optimistic activity duration estimate [Time]

m = The most likely activity duration estimate [Time]

b = The pessimistic activity duration estimate [Time]

$$Var(X) = \frac{1}{18}[(m - a)(m - b) + (b - a)^2] \tag{6}$$

where:

Var(X) = The Triangular distribution variance [Time^2]

a = The optimistic activity duration estimate [Time^2]

m = The most likely activity duration estimate [Time^2]

b = The pessimistic activity duration estimate [Time^2]

Another alternative method to calculate the framework's statistical project attributes is a Monte Carlo simulation. An example Monte Carlo simulation was performed for this praxis using Excel to randomize the critical path activities identified by the PERT analysis (i.e., it used a predefined critical path with randomized activity durations), and

its data table function was employed to perform 2,500 simulations. A Triangular distribution modeled activity duration. This distribution was selected because of the three-point activity duration estimation (Sadeghi et al., 2024), and 2,500 simulations was selected as a compromise between the 1,000 and 5,000 simulations reviewed in Sadeghi et al. (2024) and Cho and Yum (2004), respectively. The data table can be built to the preferred simulation size, and a sensitivity analysis in Chapter 4 (Results) evaluates the effect of simulation number selection on expected value and variance.

Table 3.1, column N randomized the activity duration in accordance with the Triangular distribution as found in Garvey et al. (2016). The formula used in cell *N*, and adapted to other pertinent cells in column N, was *=IFS($F2-$D2=0, $G2, $AH2<(($E2-$D2)/($F2-$D2)), $D2+(SQRT(($AH2)*($F2-$D2)*($E2-$D2))), $AH2>=(($E2-$D2)/($F2-$D2)), $F2-(SQRT((1-$AH2)*($F2-$D2)*($F2-$E2))))*. In the preceding formula, cell *AH2* generated a random number to represent the cumulative activity probability, and each activity had its own random number. The total project duration in cell *N18* of table 3.1, which was the first of the 2,500 Monte Carlo simulations, used the formula *=SUMPRODUCT($N$2:$N$17, $M$2:$M$17)*. The data table function, under *What-If Analysis* in Microsoft Excel, replicated the analysis in cell *N18* an additional 2,499 times. The resultant Monto Carlo simulation expected value and standard deviation are found in table 3.1, cells *P15* and *P18*, respectively.

The Monte Carlo simulation for this praxis was limited to critical path activities only to provide a repeatable example, but the additional step(s) of expanding the Monte Carlo simulation from critical path activities to all activities may be justified for more complex projects since it can identify the likelihood of other network completion paths being

critical (i.e., criticality index). The criticality index may help with the analysis in Section 3.4 (Model Deterministic Uncertainty) by identifying possible completion pathways.

3.4 Model Deterministic Uncertainty

The third framework step is *Model Deterministic Uncertainty*. This praxis research took inspiration from the DMDU body of knowledge (as described in Section 2.4 *Decision-Making Under Deep Uncertainty* and its subsections), specifically elements of the *Dynamic Adaptive Policy Pathways* (as further described in Kwakkel et al. (2016)) methodology to develop project completion pathways and accompanying visuals. These completion pathways and visuals become inputs into the next framework phase described in Section 3.5 (Model Risk & Opportunity). This step is responsive to the first research objective, hypothesis, and research question regarding the implementation of DMDU to a project management problem.

The first sub-step develops project completion pathways. The paths of *Activity 1 – Activity 2 – Activity 3 – Activity 5* and *Activity 1 – Activity 2 – Activity 4 – Activity 5* are example completion pathways from figure 3.2. All completion pathways may be identified for the deterministic analysis, but complex project networks may require judgement regarding which pathways to move forward. The number of pathways to move forward in the analysis is a subjective decision by the practitioner based on the level of detail they wish to pursue. As discussed in Section 3.3 (Model Statistical Uncertainty), a Monte Carlo simulation could help identify the most relevant network completion pathways. The analysis should recognize all pathways as viable alternatives regardless of their criticality index scores.

The second sub-step creates visualizations of the identified completion pathways. The visualizations should provide information about activities that intersect multiple completion pathways, like the idea of adaptation tipping points discussed in Kwakkel et al. (2016). This can be accomplished in Microsoft Excel by plotting the *Pathway ID* on the y-axis and the *Activity* on the x-axis. The result is a graphic with horizontal lines representing each completion pathway and markers on the associated activities. Since the graphic is time independent, a visual analysis shows which activities are unique or common to the completion pathways. A second visualization plotting the *Activity* on the y-axis and the *Project Step* on the x-axis shows the spread of activities at each project step. Examples of both visualizations are provided in Chapter 4 (Results).

The third sub-step uses the combined expected value of activity durations for each pathway and calculates duration as a percentage of the critical path. This sub-step, along with the earlier statistical uncertainty step, is responsive to the second research objective, hypothesis, and question regarding the integration of the statistical and deterministic analysis, and this percentage represents the total slack time available in each project pathway as compared to the critical path (i.e., 100% indicates zero slack time). A graphic with *Pathway ID* on the y-axis and *Percent of Critical Path* on the x-axis is a helpful display. This shows the available slack for the pathways, and an example is displayed in Chapter 4 (Results). The computational tool that was built to perform this and the other pieces of the analysis represent the third research objective, hypothesis, and question regarding the development of a decision-support tool.

3.5 Model Risk & Opportunity

The fourth framework step is *Model Risk & Opportunity*. The first sub-step calculates the *Activity Probability*, which defines the probability of each activity being on the completion pathway. The calculation is summarized in Equation 7 – Activity Probability.

$$Activity\ \Pr o\ bability\ =\ \frac{\#\ of\ Paths\ Activity\ \Pr esent}{\#\ of\ Total\ Paths} \quad (7)$$

where:

Activity Probability = Probability an activity is on completion pathway

# of Paths Activity Present = Number of pathways with activity present

# of Total Paths = Total number of pathways evaluated

The second sub-step calculates each activity's *Delay Impact Score* by averaging its percentage of critical path results. The third sub-step uses Equation 8 – Activity Delay Risk to calculate the *Activity Delay Risk*. This score is moved forward to the next framework phase described in Section 3.6 (Risk & Opportunity Recommendations).

$$Activity\ Delay\ Risk\ =\ (Activity\ \Pr o\ bability)\cdot(Delay\ Impact\ Score) \quad (8)$$

where:

Activity Delay Risk = Activity Probability * Delay Impact Score

Activity Probability = Probability an activity is on completion pathway

Delay Impact Score = Average of activity percentage of critical path results

3.6 Risk & Opportunity Recommendations

The fifth framework step is *Risk & Opportunity Recommendations*. This step ranks the Activity Delay Risk values, and their associated activities, from highest to lowest.

This prioritized activity list is the culmination of the framework, and it provides an initial recommendation that can help with risk and opportunity prioritization and management.

This praxis does not prescribe a risk and opportunity management approach; it envisions integrating the risk prioritization information from the framework into current organizational risk and opportunity management processes. Three recommendations for organizations implementing risk management processes are summarized below.

Recommendation 1: If using risk matrices, adhere to the three axioms of weak consistency, betweenness, and consistent coloring presented by Cox (2008). The axioms can reduce the variability and/or irregularity that is present in some risk matrices.

Recommendation 2: Reviewing the *set of triplets* idea presented by Kaplan and Garrick (1981) is a first step when developing quantitative risk management practices.

Recommendation 3: The PMI (2021) provides five strategies to cope with risks (labeled threats by PMI): avoid, escalate, transfer, mitigate, and accept, and five strategies to cope with opportunities: exploit, escalate, share, enhance, and accept.

3.7 Monitor & Compare

The sixth framework step is *Monitor & Compare*. This step recognizes that project attributes may change during project execution, which has implications for the results of this framework and the accompanying risk and opportunity analysis. To account for this, the project attributes (e.g., activity duration estimates, selected statistical distribution parameters, and/or critical path) should be reviewed against the initial framework assumptions at project activity intersections and updates to the framework pursued if the comparison yields differences that invalidate its results. Discretion is required to

determine when updates are needed and which steps should be reanalyzed (i.e., not all framework steps may need to be repeated).

3.8 Framework Summary

The proposed framework combines industry-standard practices and methodologies in project and engineering management to evaluate a network diagram and provide prioritized activity-level risk management recommendations. The framework meets the principles presented in Section 3.1 (Introduction), which include responsiveness to the praxis research goals, development of a holistic approach, flexibility in computational tools and underlying methodology selection, and implementation that mirrors project time and budget constraints. A review of the praxis research questions provides more justification on how the methodology is responsive to the research goals.

Research Question 1: How can definitions and DMDU methods (e.g., Dynamic Adaptive Policy Pathways) be applied early in the project management process to evaluate project uncertainty?

The definitions from Chapter 2 (Literature Review) are incorporated into the framework, which takes inspiration from the DMDU Dynamic Adaptive Policy Pathway method through development of project network completion pathways and associated visualizations. The framework recognizes that a project's critical path may change, and it recommends reviewing framework decisions and output at project activity intersections, which are analogous to the adaptation tipping points from the policy pathway method.

Research Question 2: How can a task- and project-level statistical analysis (e.g., PERT and Monte Carlo Simulation) be incorporated with DMDU methods in the project uncertainty evaluation?

The project duration expected values from the *Model Statistical Uncertainty* framework step are input into the *Model Deterministic Uncertainty* step; this represents the beginning of the DMDU-inspired methodology. The framework's final output is a prioritized list of activities (i.e., sources) for risk and opportunity management.

Research Question 3: How can a decision-support tool that is informed by the DMDU and statistical methods facilitate development of project risk and opportunity recommendations?

The framework's DMDU-inspired *Model Deterministic Uncertainty* step develops information that the *Model Risk & Opportunity* and the *Risk & Opportunity Recommendations* steps are used to develop the final prioritized activity list that informs a project's risk and opportunity analysis.

Chapter 4: Results

4.1 Introduction

The chapter is organized into six sections, excluding the introduction. The case study comprises the next section, with subsections including statistical uncertainty results, deterministic uncertainty results, case study validation, methodology integration, and activity risk & opportunity prioritization. Sections 4.3 through 4.6 discuss study principles; risk and opportunity analysis; problem and thesis statements; and research objectives, hypotheses, and questions, respectively.

4.2 Case Study Description

The network diagram and attribute information used for this case study is shown in figure 4.1 and was adapted from Van Slyke (1963) with permission from RAND Corporation. The diagram was selected because it represented a general network diagram that was not attached to a specific project type; it incorporated activity duration estimates and resultant statistical analysis data; and it included a variation of completion pathways (nine) to test the praxis framework through the statistical uncertainty, deterministic uncertainty, and case study validation phases.

The available tools used to perform project management functions, including developing network diagrams, have evolved and improved over time, but the fundamental structure of the diagram has not changed significantly. This means the selected diagram's age was not considered a negative outcome, and the framework can be applied to both old and new network diagrams. More importantly, a practitioner must

recognize the diagram type (i.e., activity-on-arrow vs. activity-on-node) to apply the framework correctly, as discussed in section 3.2 (Project Diagramming).

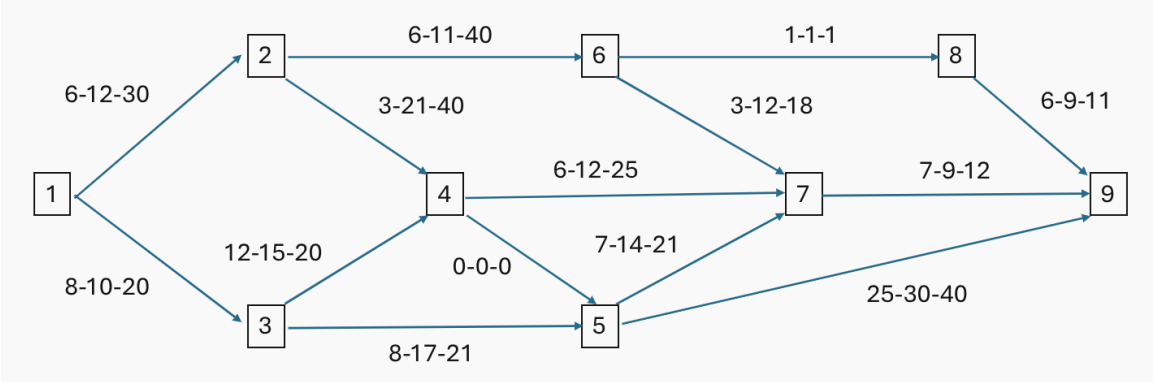

Figure 4.1. Activity-on-arrow diagram with optimistic, most likely, and pessimistic activity completion estimates (left to right, respectively). The network diagram was adapted from Van Slyke (1963) with permission.

4.2.1 Case Study Statistical Uncertainty Results

The project duration statistical results rely on the selection of a statistical method and activity-level duration estimates. The results provide insight into project uncertainty and are useful when making resource decisions about a project, but managers must recognize these results are not absolute, and project adjustments may result in new duration estimates. Three statistical techniques were modeled as part of the praxis to show possible options and confirm that distribution selection influences the results. It is up to the practitioner to determine whether to perform one statistical analysis or if the insight gained from multiple statistical analyses is helpful to the study. A project or engineering manager must understand the common distribution characteristics to make an informed distribution(s) selection for their project.

Table 4.1 contains activity-level information including duration estimates, Program Evaluation and Review Technique (PERT) and Triangular distribution statistical

parameters, critical path identification, and a summary of the first iteration of 2,500 Monte Carlo simulations. The table also provides project-level statistical summaries for the activities, PERT and Triangular distribution, and Monte Carlo simulation in orange.

The project-level duration calculations in table 4.1 show the PERT and Triangular distribution expected values are 66.00 and 69.00, respectively, and the standard deviations are 7.76 and 9.63, respectively. The percentage difference calculations for these expected values and standard deviations are 4.4% and 21.5%, respectively. The percentage difference calculation for the table 4.1 PERT and Triangular distribution variance values is 42.5%, showing that distribution differences may be better understood by evaluating both standard deviation and variance.

These results are an example of the differences that can be expected in statistical distribution calculations, and the example solidifies the recommendation provided in Section 4.2.1 (Case Study Statistical Uncertainty Results) that a practitioner should understand the statistical distribution assumptions before applying it to a project. The distribution selection may be partially informed by a practitioner's risk tolerance. For this example, selecting the Triangular distribution provides a more conservative duration estimate than the PERT analysis due to a larger expected value and standard deviation.

The expected values for the Triangular distribution and Monte Carlo simulation were 69.00 and 69.21, respectively, and standard deviation values were 9.63 and 9.82, respectively. These values' agreement matches the Monte Carlo simulation assumptions from Section 3.3 (Model Statistical Uncertainty) that activities were modeled using a Triangular distribution and the critical path remained static during the simulation. A Monte Carlo simulation that includes the critical path calculation for each simulation will

have additional statistical variation. This adds complexity to the analysis but may help identify other completion pathways for analysis, as discussed at the end of Section 3.3.

Table 4.1. Table showing activity and project-level statistical analysis. The activity duration estimates were adapted from Van Slyke (1963) with permission.

Activity	From	To	Optimistic Estimate	Most Likely Estimate	Pessimistic Estimate	PERT Expected Value	PERT Variance	PERT Std Dev	Triangular Expected Value	Triangular Variance	Triangular Std Dev	Critical Path (1=Yes, 0=No)	Monte Carlo Duration
STARTto1	START	1	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00
1to2	1	2	6	12	30	14.00	16.00	4.00	16.00	26.00	5.10	1	19.76
1to3	1	3	8	10	20	11.33	4.00	2.00	12.67	6.89	2.62	0	9.89
2to6	2	6	6	11	40	15.00	32.11	5.67	19.00	56.17	7.49	0	17.94
2to4	2	4	3	21	40	21.17	38.03	6.17	21.33	57.06	7.55	1	19.11
3to4	3	4	12	15	20	15.33	1.78	1.33	15.67	2.72	1.65	0	14.65
3to5	3	5	8	17	21	16.17	4.69	2.17	15.33	7.39	2.72	0	16.45
4to7	4	7	6	12	25	13.17	10.03	3.17	14.33	15.72	3.97	0	12.15
4to5	4	5	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00
5to7	5	7	7	14	21	14.00	5.44	2.33	14.00	8.17	2.86	0	20.21
5to9	5	9	25	30	40	30.83	6.25	2.50	31.67	9.72	3.12	1	37.23
6to8	6	8	1	1	1	1.00	0.00	0.00	1.00	0.00	0.00	0	1.00
6to7	6	7	3	12	18	11.50	6.25	2.50	11.00	9.50	3.08	0	8.33
7to9	7	9	7	9	12	9.17	0.69	0.83	9.33	1.06	1.03	0	10.30
8to9	8	9	6	9	11	8.83	0.69	0.83	8.67	1.06	1.03	0	8.19
9toEND	9	END	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	1	0.00
TOTAL			34.00	63.00	110.00	66.00	60.28	7.76	69.00	92.78	9.63		76.10

Nodes	Net Flow		Supply/ Demand
START	1	=	1
1	0	=	0
2	0	=	0
3	0	=	0
4	0	=	0
5	0	=	0
6	0	=	0
7	0	=	0
8	0	=	0
9	0	=	0
END	-1	=	-1

Monte Carlo Expected Value
69.21

Monte Carlo Std Dev
9.82

Figures 4.2, 4.3, and 4.4 confirm the f(x) (i.e., probability density function) and F(x) (i.e., cumulative distribution function) summary results presented in table 4.1 for the PERT, Triangular distribution, and Monte Carlo simulation, respectively, and figures 4.5 and 4.6 provide visual confirmation of the differences in f(x) and F(x) probabilistic duration estimates for different statistical methods, respectively. Figures 4.5 and 4.6 also show the previously discussed agreement between the Triangular distribution and Monte Carlo simulation.

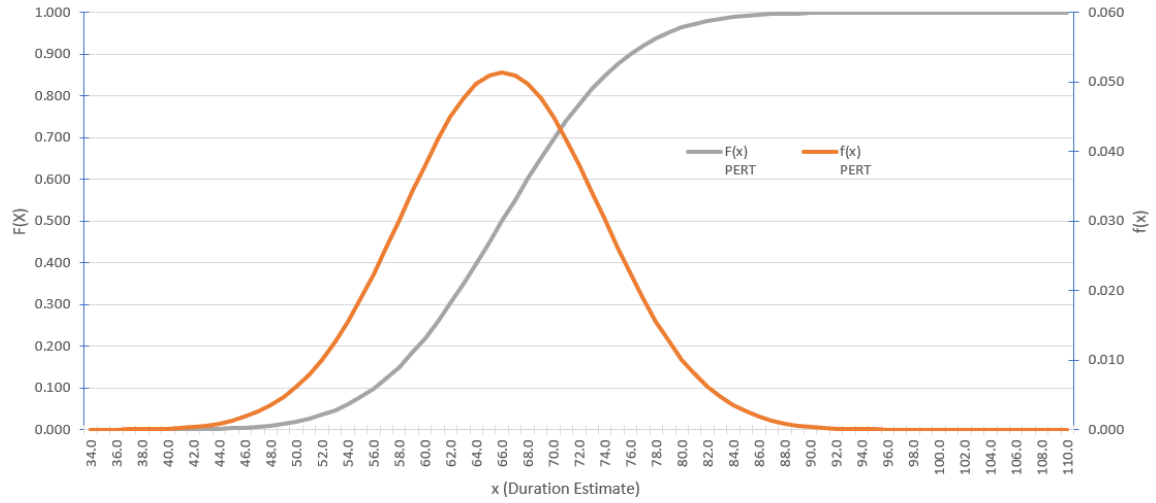

Figure 4.2. Total project time F(x) and f(x) distributions for the PERT analysis. The project attributes were adapted from Van Slyke (1963) with permission.

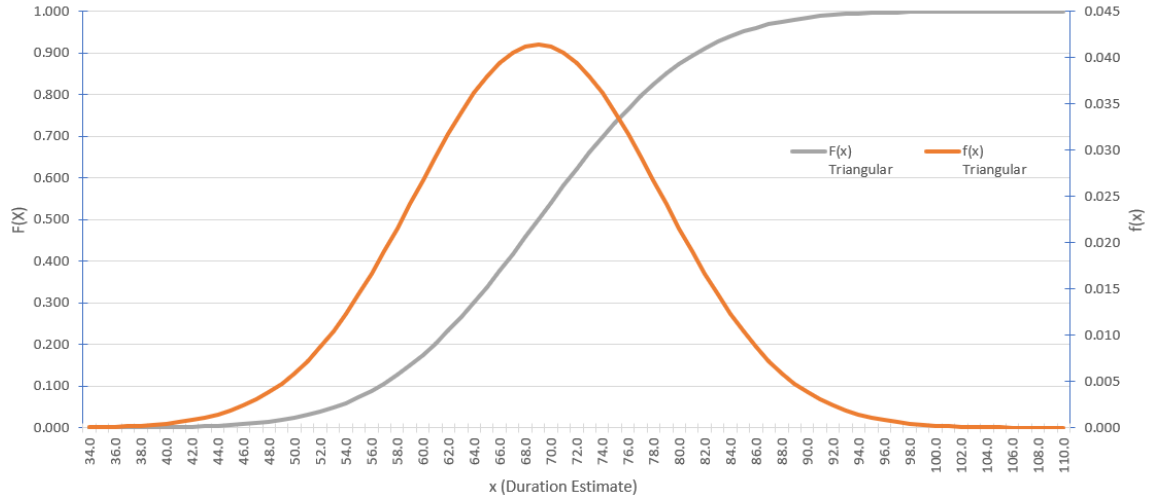

Figure 4.3. Total project time F(x) and f(x) distributions for the Triangular distribution. The project attributes were adapted from Van Slyke (1963) with permission.

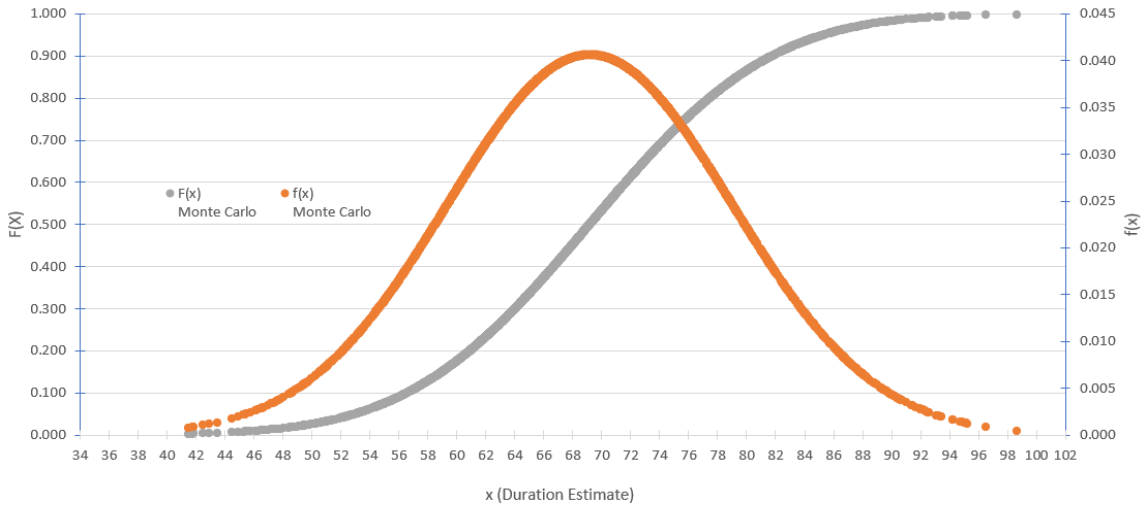

Figure 4.4. Total project time F(x) and f(x) distributions for the Monte Carlo simulation. The project attributes were adapted from Van Slyke (1963) with permission.

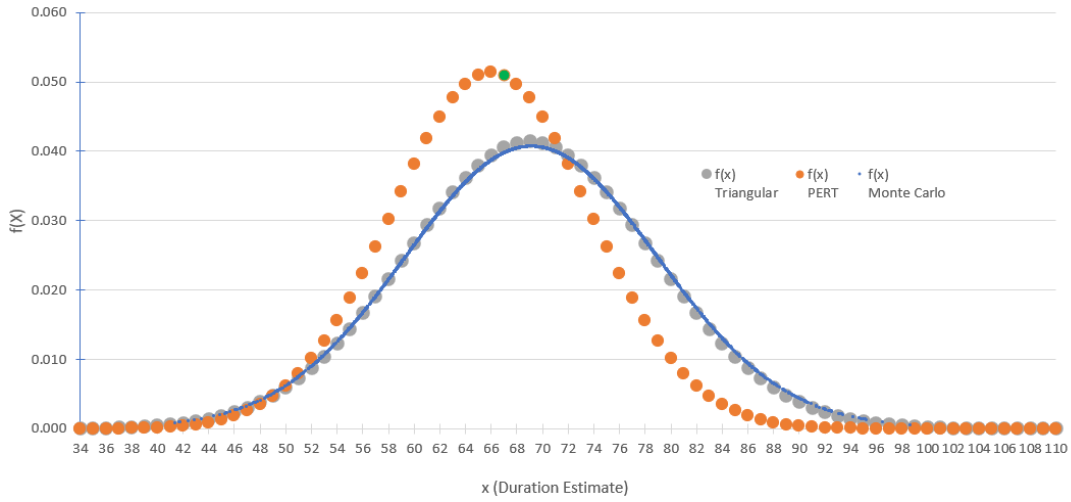

Figure 4.5. Total project time f(x) distributions comparison for the Triangular distribution, PERT analysis, and Monte Carlo simulation. The project attributes were adapted from Van Slyke (1963) with permission.

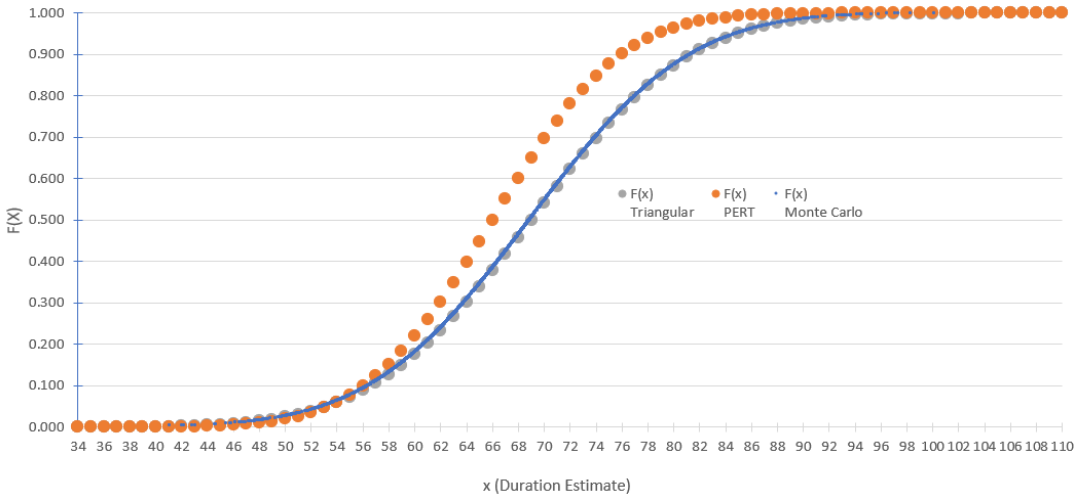

Figure 4.6. Total project time F(x) distribution comparison for the Triangular distribution, PERT analysis, and Monte Carlo simulation. The project attributes were adapted from Van Slyke (1963) with permission.

4.2.2 Case Study Deterministic Uncertainty Results

Table 4.2 lists the nine completion pathways for the network diagram in figure 4.1 (column R). The table also lists each pathway's PERT expected value (i.e., Duration Estimate) in column S, and the percentage of time compared to the critical path (column T), as defined in Section 3.4 (Model Deterministic Uncertainty). The critical path (Pathway ID #4) is shown in bold. This table represents three deterministic methodology assumptions. First, each pathway is viable and could be the actual completion pathway. Second, the number of pathways an activity shares increases the probability that activity will cause a project delay. Third, as a respective pathway's duration approaches the critical path's duration, the potential for schedule delay (i.e., project impact) increases.

Table 4.2. Table shows the nine completion pathways, durations, and percentages of the critical path. The project attributes were adapted from Van Slyke (1963) with permission. The Duration Estimate and Percent of Critical Path values were rounded to the nearest whole number.

Q	R	S	T
Pathway ID #	**Pathway Nodes**	**Duration Estimate (Expected)**	**Percent of Critical Path**
1	START --> 1 --> 2 --> 6 --> 8 --> 9 --> END	50	75%
2	START --> 1 --> 2 --> 6 --> 7 --> 9 --> END	50	75%
3	START --> 1 --> 2 --> 4 --> 7 --> 9 --> END	58	87%
4	**START --> 1 --> 2 --> 4 --> 5 --> 9 --> END**	**66**	**100%**
5	START --> 1 --> 2 --> 4 --> 5 --> 7 --> 9 --> END	58	88%
6	START --> 1 --> 3 --> 4 --> 5 --> 7 --> 9 --> END	48	73%
7	START --> 1 --> 3 --> 4 --> 7 --> 9 --> END	49	74%
8	START --> 1 --> 3 --> 4 --> 5 --> 9 --> END	58	87%
9	START --> 1 --> 3 --> 5 --> 9 --> END	58	88%

Table 4.3 provides the *Activity Probability* (column D), *Delay Impact Score* (column N), and the *Activity Delay Risk* (column O) calculations. These terms were defined in Section 3.5 (Model Risk & Opportunity). The Activity Delay Risk calculations ranged from 0.08 to 0.83, with higher values representing higher delay risk. The 0.83 was calculated for both the *STARTto1* and *9toEND* activities. These activities are the first and last activities, respectively, and have an Activity Probability equal to one since they are present on all pathways, which results in a highly ranked Activity Delay Risk. The removal of these activities from the analysis may be justified; therefore, they have been grayed out on table 4.3. Their removal results in a smaller range of 0.08 to 0.47. Section 4.2.4 (Case Study Methodology Integration) will explore activity removal as part of the prioritization discussion.

Table 4.3. Table of deterministic uncertainty information including the Activity Delay Risk calculation. The project attributes were adapted from Van Slyke (1963) with permission.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Activity	Number of Paths	Total Pathways	Activity Probability	Pathway ID #1	Pathway ID #2	Pathway ID #3	Pathway ID #4	Pathway ID #5	Pathway ID #6	Pathway ID #7	Pathway ID #8	Pathway ID #9	Delay Impact	Activity Delay Risk
2	STARTto1	9	9	100%	75%	75%	87%	100%	88%	73%	74%	87%	88%	83%	0.83
3	1to2	5	9	56%	75%	75%	87%	100%	88%					85%	0.47
4	1to3	4	9	44%						73%	74%	87%	88%	81%	0.36
5	2to6	2	9	22%	75%	75%								75%	0.17
6	2to4	3	9	33%			87%	100%	88%					92%	0.31
7	3to4	3	9	33%						73%	74%	87%		78%	0.26
8	3to5	1	9	11%									88%	88%	0.10
9	4to7	2	9	22%			87%				74%			81%	0.18
10	4to5	4	9	44%				100%	88%	73%		87%		87%	0.39
11	5to7	2	9	22%					88%	73%				80%	0.18
12	5to9	3	9	33%				100%				87%	88%	92%	0.31
13	6to8	1	9	11%	75%									75%	0.08
14	6to7	1	9	11%		75%								75%	0.08
15	7to9	5	9	56%		75%	87%		88%	73%	74%			79%	0.44
16	8to9	1	9	11%	75%									75%	0.08
17	9toEND	9	9	100%	75%	75%	87%	100%	88%	73%	74%	87%	88%	83%	0.83

The *node* and *pathway duration* for each completion pathway are plotted on the x-axis in figures 4.7 and 4.8, respectively, and in both cases the *Pathway ID* is plotted on the y-axis. Figure 4.7 visualizes the Activity Probability calculations from table 4.3 by showing the pathways that share nodes. The fact that all pathways contain *STARTto1* and *9toEND* activities can be seen in the figure. Additionally, the figure shows the most prevalent activities on the completion pathways without calculations and verifies table 4.3 calculations. Figure 4.8 shows the critical path calculations from table 4.2, and collectively the figures apply elements of Decision-Making under Deep Uncertainty (DMDU) and visualize the three assumptions listed at the beginning of this section.

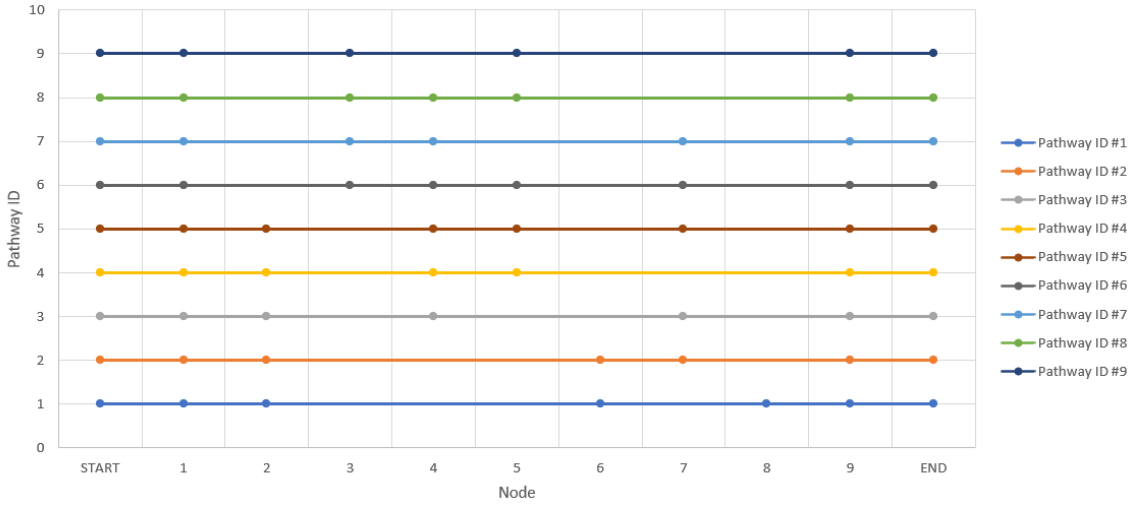

Figure 4.7. Activity Probability from table 4.3 (Pathway ID (y-axis) vs. Node (x-axis)). The project attributes were adapted from Van Slyke (1963) with permission.

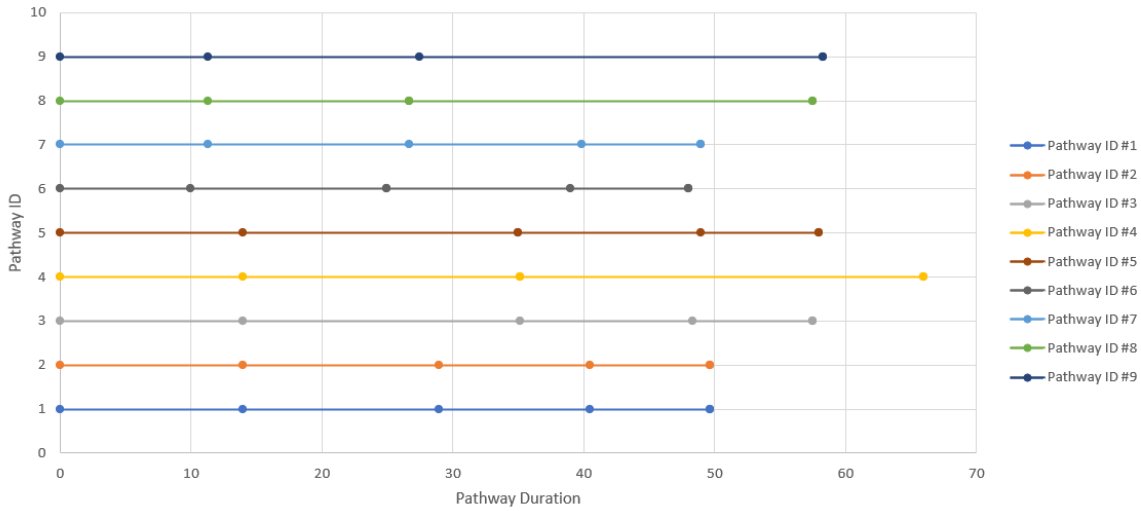

Figure 4.8. Percentage of critical path from table 4.2 (Pathway ID (y-axis) vs. Duration (x-axis)). The project attributes were adapted from Van Slyke (1963) with permission.

4.2.3 Case Study Validation

The development of a quantitative method for the activity prioritization of project risk management was the goal of this praxis research. An industry-standard process to validate this framework was not found, so methods were developed to better understand the framework's statistical and deterministic uncertainty methods. The statistical analysis validation focused on a comparison to published literature and a sensitivity analysis to verify the model results and examine how the number of simulations affected the Monte Carlo simulation results, respectively. The deterministic analysis validation developed an alternative slack time methodology, applied it to the network diagram in figure 4.1, used its results to calculate new Activity Delay Risk values, and compared these values to the calculations from the original praxis methodology. Future research to validate the effectiveness of the framework against empirical data could be undertaken and provide useful perspective, as described in sections 1.8 (Research Limitations) and 5.3 (Future Research).

The first validation for the statistical uncertainty step used PERT-calculated expected value and variance from the network diagram in Van Slyke (1963). The PERT expected value and variance modeled values of 66.0 and 60.28 compared to published values in Van Slyke (1963) of 66.0 and 60.27, respectively. Triangular distribution information for the same network diagram was provided in an additional publication by Van Slyke (1963). The Triangular distribution modeled values for expected value and variance of 69.0 and 92.78 compared to published values in Van Slyke (1963) of 69.0 and 92.77, respectively.

The second validation for the statistical uncertainty step was between the Monte Carlo simulation and the Triangular distribution model. The Monte Carlo simulation assumed a stationary critical path for all simulations and modeled the critical path activity times using the Triangular distribution, as described in Section 3.3 (Model Statistical Uncertainty). These assumptions allowed for a comparison of the Monte Carlo simulation expected value and standard deviation to the Triangular distribution calculations. The Monte Carlo simulation expected value and standard deviation values of 69.21 and 9.82 from table 4.1 compared to Triangular distribution values of 69.00 and 9.63, respectively.

The third validation for the statistical uncertainty step was a sensitivity analysis on the number of Monte Carlo simulations. The expected value and standard deviation were compared in increments of 250 for the number of simulations up to 2,500. Tables 4.4 and 4.5 categorize five Monte Carlo simulation trials' expected value and standard deviation by number of simulations and ranges, respectively. Figures 4.9 and 4.10 visualize the variation in expected value and standard deviation by number of simulations, respectively.

The five-trial maximum and minimum ranges for the expected value were 1.17 (Trial 4) and 0.23 (Trial 3), respectively. These represented percentage of average values (i.e., the percentage of the range to the average) of 1.70% and 0.33%, respectively, as reported in table 4.4. The overall maximum and minimum expected values from table 4.5 were 69.50 and 68.98, which resulted in a cross-trial range of 0.52. For standard deviation, the five-trial maximum and minimum ranges were 0.69 (Trial 5) and 0.20 (Trial 4), respectively. These represented percentage of average values of 7.20% and 2.07%,

respectively, as reported in table 4.4. The overall maximum and minimum values from table 4.5 were 10.07 and 9.61, which resulted in a cross-trial range of 0.46.

An evaluation of the cross-trial results in figures 4.9 and 4.10 shows the widest spread between values at the lowest number of simulations (i.e., 250 simulations) for the expected value and standard deviation. The spread between simulations generally reduces as the simulation number increases. This trend does not guarantee the lowest spread occurred at 2,500 simulations, but it supports the idea that the variability in Monte Carlo expected value and standard deviation decreases as the simulations number increases.

Table 4.4. Monte Carlo simulation expected value and standard deviation comparison by number of simulations for five Monte Carlo simulation trials.

	A	B	C	D	E	F	G	H	I	J	K
1		Trial 1		Trial 2		Trial 3		Trial 4		Trial 5	
2	Number of Simulations	Monte Carlo Expected Value	Monte Carlo Standard Deviation	Monte Carlo Expected Value	Monte Carlo Standard Deviation	Monte Carlo Expected Value	Monte Carlo Standard Deviation	Monte Carlo Expected Value	Monte Carlo Standard Deviation	Monte Carlo Expected Value	Monte Carlo Standard Deviation
3	250	69.08	9.34	68.87	9.17	68.98	9.89	67.82	9.72	69.50	10.07
4	500	68.91	9.55	68.89	9.42	69.19	9.56	68.10	9.87	69.47	9.93
5	750	68.84	9.50	69.00	9.58	69.12	9.57	68.42	9.75	68.90	9.82
6	1000	68.73	9.59	69.13	9.64	69.21	9.57	68.61	9.74	69.05	9.74
7	1250	68.85	9.51	69.14	9.59	69.18	9.58	68.60	9.67	69.39	9.62
8	1500	68.96	9.61	69.01	9.69	69.00	9.63	68.78	9.74	69.48	9.54
9	1750	69.15	9.53	69.08	9.66	69.13	9.65	68.80	9.78	69.41	9.48
10	2000	69.16	9.52	69.15	9.67	69.01	9.74	68.98	9.81	69.40	9.43
11	2250	69.21	9.55	69.25	9.54	69.04	9.68	68.95	9.76	69.27	9.42
12	2500	69.18	9.53	69.29	9.53	69.05	9.65	68.89	9.70	69.30	9.38
13	Maximum	69.21	9.61	69.29	9.69	69.21	9.89	68.98	9.87	69.50	10.07
14	Minimum	68.73	9.34	68.87	9.17	68.98	9.56	67.82	9.67	68.90	9.38
15	Range	0.48	0.26	0.41	0.52	0.23	0.33	1.17	0.20	0.59	0.69
16	Average	69.01	9.52	69.08	9.55	69.09	9.65	68.60	9.76	69.32	9.64
17	Range % of Average	0.70%	2.76%	0.60%	5.43%	0.33%	3.47%	1.70%	2.07%	0.85%	7.20%

Table 4.5. Monte Carlo simulation expected value and standard deviation maximum and minimum ranges and values for five Monte Carlo simulation trials.

M	N
All Trials	
Expected Value	Std Dev
Maximum Range	
1.17	0.69
Minimum Range	
0.23	0.20
Maximum Value	
69.50	10.07
Minimum Value	
68.98	9.61

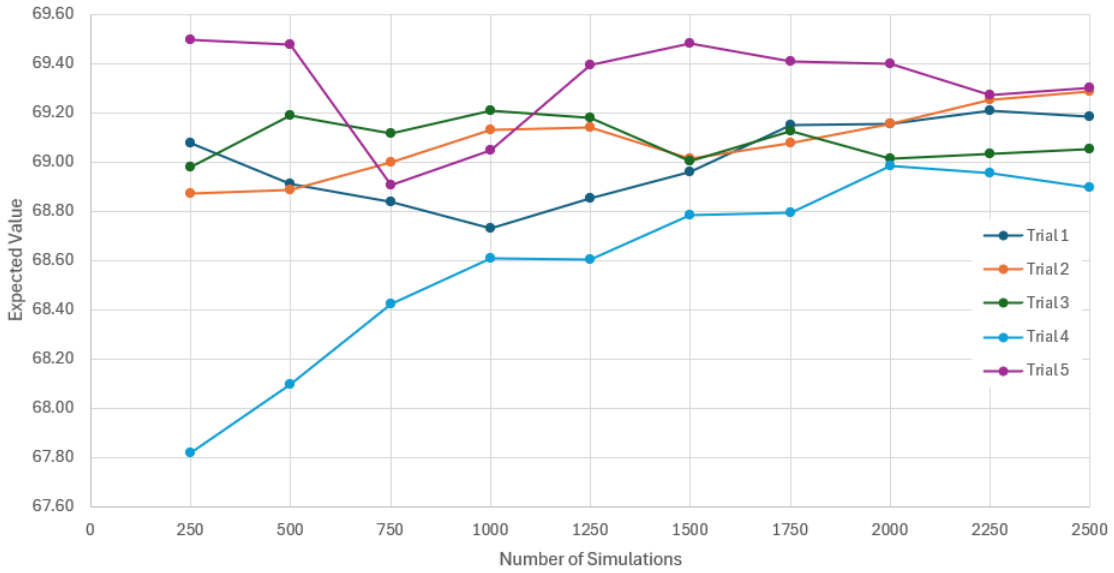

Figure 4.9. Variation in the Monte Carlo simulation expected value by number of simulations for five Monte Carlo simulation trials.

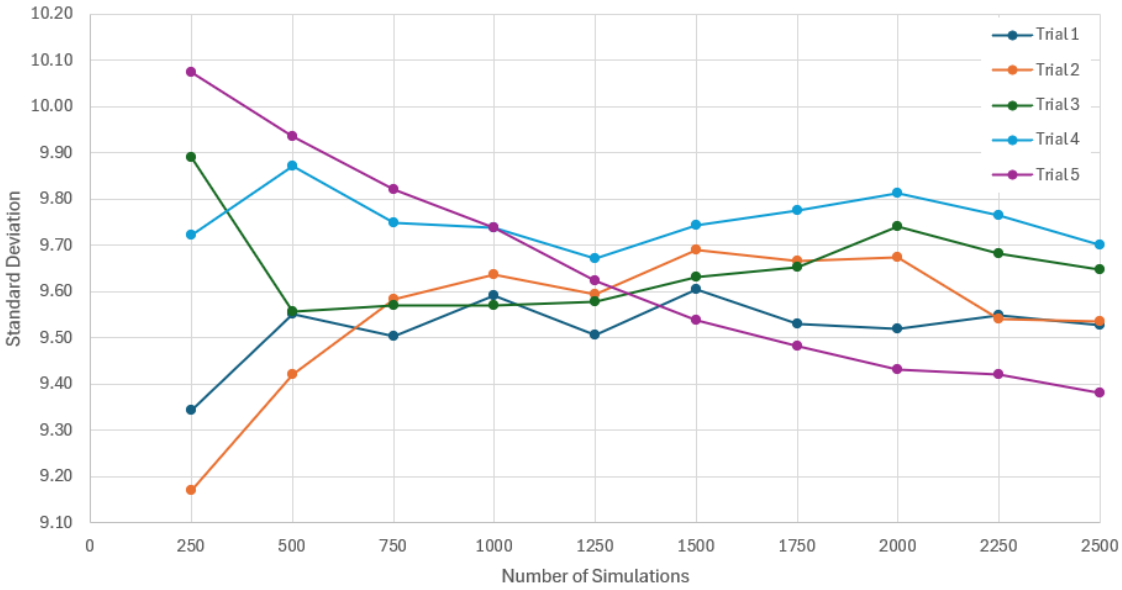

Figure 4.10. Variation in the Monte Carlo simulation standard deviation by number of simulations for five Monte Carlo simulation trials.

Recognizing that the pathway map analysis relied on the calculation of slack time, as described in Chapter 3 (Methodology), an alternate slack time methodology was applied to the network diagram in figure 4.1 and compared to the deterministic uncertainty analysis. This process used project management calculations for early start, early finish, late start, and late finish to calculate activity slack time, as described by Pinto (2020). These slack times were treated as analogous to the percentage of critical path calculation from Chapter 3 (Methodology) and applied to the praxis deterministic methodology to calculate Activity Probability, Delay Impact, and Activity Delay Risk. These Activity Delay Risk calculations were prioritized and compared to the Activity Delay Risk calculations using the process identified in Chapter 3 (Methodology).

Table 4.6 provides the activity slack time calculations using the alternate methodology (Pinto,2020), and activities on the critical path are identified by an activity slack time calculation of zero. The table indicates that activities *STARTto1 --> 1to2 --> 2to4 --> 4to5 --> 5to9 --> 9toEND* are the critical path. This verifies the critical path calculations in tables 4.1 and 4.2 shown by activity and nodes, respectively. The critical path represented by node in table 4.2 reads *START --> 1 --> 2 --> 4 --> 5 --> 9 --> END*.

Table 4.6. Activity slack time calculations for alternate praxis framework methodology. Activities on the critical path are identified by an activity slack time calculation of zero.

	A	B	C	D	E	F	G	H
1	Activity	PERT Expected Value	Early Start	Early Finish	Late Start	Late Finish	Slack LF-EF	Slack LS-ES
2	STARTto1	0	0	0	0	0	0	0
3	1to2	14	0	14	0	14	0	0
4	1to3	11	0	11	9	20	9	9
5	2to6	15	14	29	30	45	16	16
6	2to4	21	14	35	14	35	0	0
7	3to4	15	11	27	20	35	9	9
8	3to5	16	11	28	27	43	15	15
9	4to7	13	35	48	44	57	9	9
10	4to5	0	35	35	35	35	0	0
11	5to7	14	35	49	43	57	8	8
12	5to9	31	35	66	35	66	0	0
13	6to8	1	29	30	56	57	27	27
14	6to7	12	29	41	45	57	16	16
15	7to9	9	49	58	57	66	8	8
16	8to9	9	30	39	57	66	27	27
17	9toEND	0	66	66	66	66	0	0

Table 4.7 lists Activity Probability, Delay Impact, Activity Delay Risk, and supporting information for the alternate methodology calculations. Table 4.8 shows these Activity Delay Risk values after prioritization (i.e., Validation) and compares them to the original praxis methodology Activity Delay Risk values (i.e., Deterministic) from table 4.3. In both cases the first and last activities are ranked first and second, respectively, and they are grayed out in both tables. When comparing the two methods, the *2to4* and *5to9*, *4to7* and *5to7*, and *6to7* and *6to8* are immediately reversed in the prioritization order, but in the case of the Deterministic (original praxis methodology) values the Activity Delay Risk calculations are equal; therefore, they could be ordered either way. For the validation case, the *2to4* and *5to9* calculations are equal; the 5*to7* and 4*to7* calculations

are 13.0 and 12.8, respectively; and the *6to7* and *6to8* calculations are 5.5 and 4.3, respectively. Two conclusions from this deterministic methodology validation:

1. The original praxis or alternate methodologies can be used to calculate Activity Delay Risk, so a practitioner could select either method for their deterministic analysis.
2. The original praxis deterministic methodology uses a *percentage of critical path* slack time calculation, which simplifies the calculations compared to calculating activity slack time.

Table 4.7. Activity Probability, Delay Impact, Activity Delay Risk, and supporting information for the alternate methodology, represented as *Validation* in Table 4.8.

J	K	L	M	N	O	P	Q
Activity	Number of Paths	Total Pathways	Activity Probability	Critical Path	Slack LF-EF	Delay Impact	Activity Delay Risk
STARTto1	9	9	100%	66	0	66	66.0
1to2	5	9	56%	66	0	66	36.7
1to3	4	9	44%	66	9	58	25.6
2to6	2	9	22%	66	16	50	11.0
2to4	3	9	33%	66	0	66	22.0
3to4	3	9	33%	66	9	58	19.2
3to5	1	9	11%	66	15	51	5.6
4to7	2	9	22%	66	9	58	12.8
4to5	4	9	44%	66	0	66	29.3
5to7	2	9	22%	66	8	58	13.0
5to9	3	9	33%	66	0	66	22.0
6to8	1	9	11%	66	27	39	4.3
6to7	1	9	11%	66	16	50	5.5
7to9	5	9	56%	66	8	58	32.4
8to9	1	9	11%	66	27	39	4.3
9toEND	9	9	100%	66	0	66	66.0

Table 4.8. A comparison of the Activity Delay Risk values for the alternate methodology (i.e., Validation) and the original praxis methodology (i.e., Deterministic).

D	E	F	G
Prioritized Activity Lists			
Deterministic		Validation	
Activity	Delay Risk	Activity	Delay Risk
STARTto1	0.83	STARTto1	66.0
9toEND	0.83	9toEND	66.0
1to2	0.47	1to2	36.7
7to9	0.44	7to9	32.4
4to5	0.39	4to5	29.3
1to3	0.36	1to3	25.6
5to9	0.31	2to4	22.0
2to4	0.31	5to9	22.0
3to4	0.26	3to4	19.2
4to7	0.18	5to7	13.0
5to7	0.18	4to7	12.8
2to6	0.17	2to6	11.0
3to5	0.10	3to5	5.6
6to8	0.08	6to7	5.5
6to7	0.08	6to8	4.3
8to9	0.08	8to9	4.3

4.2.4 Case Study Methodology Integration

Table 4.9 summarizes the PERT, Triangular distribution, and Monte Carlo simulation statistical uncertainty duration analyses. Table 4.9 values for expected value and standard deviation match table 4.1 values, respectively. A calculation of three standard deviations above and below the expected value for each statistical case is included in table 4.9. Three standard deviations was selected since the probability of a value being within three standard deviations of the expected value for a normal distribution is 99.7% (Garvey et al., 2016). The PERT, Triangular distribution, and Monte Carlo simulation yielded duration ranges of 42.71 to 89.29, 40.10 to 97.90, and 39.73 to 98.68, respectively. The difference between the PERT and Triangular distribution lower and upper durations are 2.61 and –8.61, respectively. The difference between the Triangular distribution and Monte Carlo simulation lower and upper duration values are 0.37 and –0.78, respectively.

The use of the Triangular distribution for activity modeling within the Monte Carlo simulation resulted in the low magnitude duration differences.

Table 4.9. Statistical uncertainty methodology summary for the PERT, Triangular distribution, and Monte Carlo simulation.

	A	B
1	**Statistical Uncertainty Summary**	
2	Most Likely Duration Estimate	63.00
3		
4	PERT Expected Value	66.00
5	PERT Std Dev	7.76
6	**PERT -3 Std Dev**	**42.71**
7	**PERT +3 Std Dev**	**89.29**
8		
9	Triangular Expected Value	69.00
10	Triangular Std Dev	9.63
11	**Triangular -3 Std Dev**	**40.10**
12	**Triangular +3 Std Dev**	**97.90**
13		
14	Monte Carlo Expected Value	69.21
15	Monte Carlo Std. Dev.	9.82
16	**Monte Carlo -3 Std Dev**	**39.73**
17	**Monte Carlo +3 Std Dev**	**98.68**

Table 4.10 displays the framework's prioritized Activity Delay Risk calculations. The table informs where to focus activity-level risk and opportunity management, and it represents the culmination of the praxis deterministic methodology and the overall framework. The Activity Delay Risk calculation recognizes that any network pathway could become the completion pathway and that the presence of activities on network pathways varies. The praxis framework uses these attributes to provide a holistic approach to risk and opportunity management by focusing on a suite of potential completion pathways, rather than only on the critical path.

Table 4.10. Prioritized Activity Delay Risk calculations for the original praxis deterministic methodology.

I	J
Deterministic Activity Delay Risk	
Activity	**Delay Risk**
STARTto1	0.83
9toEND	0.83
1to2	0.47
7to9	0.44
4to5	0.39
1to3	0.36
5to9	0.31
2to4	0.31
3to4	0.26
4to7	0.18
5to7	0.18
2to6	0.17
3to5	0.10
6to8	0.08
6to7	0.08
8to9	0.08

4.2.5 Case Study Risk & Opportunity Prioritization

The network diagram used for this case study was selected based on its ability to test the praxis framework, but it lacked the necessary project attributes (i.e., project type, activity names, etc.) to perform a risk and opportunity analysis. While separate from the first case study, Section 4.4 (Risk & Opportunity Discussion) discusses the development of risk statements, risk parameters (i.e., probability and impact), and a risk register for those interested or new to risk management.

This praxis framework provides an activity prioritization approach for risk and opportunity management early in the project management process. The framework advises but requires expert judgement to interpret the results and forge a risk and opportunity management plan. One example from this case study is the inclusion, or

exclusion, of the first and last activities from the analysis (included but grayed out in table 4.10). Both activities are present on all nine network pathways, which results in a high Activity Delay Risk and places them at the top of the priority list. In some cases, practitioners may determine that those activities should remain in the analysis while in other cases removing the activities may be the determined path forward. Expert interpretations will be needed to answer these types of project-specific questions and implement the praxis framework. In many cases, there may not be a *right* answer.

4.3 Study Principles

Several important principles for the praxis framework development included:

1. The framework is responsive to the praxis problem statement, thesis statement, research objectives, and associated research questions and hypotheses.
2. The framework represents a holistic approach to the evaluation of project uncertainty to prioritize activities for the development of event-driven risk and opportunity recommendations.
3. The framework is unbiased regarding the selection of computational evaluation tools and statistical methodologies.
4. The framework focuses on industry-standard practices, where possible, to give practitioners familiarity and benchmarks with the underlying methodologies.
5. The recommendation is to carry out the framework at the beginning of a project with follow-up iterations of required steps as needed.
6. The framework can be implemented to fit within a project's time and budget constraints yet still provides useful uncertainty and prioritization information.

Considering the above principles, the following section describes how practitioners could use the framework to make prioritized decisions about risk management.

4.4 Risk & Opportunity Discussion

This section presents ideas to write good risks (and opportunities) and aligns the process with the praxis framework, respectively. Combined with information from Section 3.6 (Risk & Opportunity), the sections provide guidance for practitioners with no current risk management paradigm, that are interested in pursuing a different approach, and/or are new to risk management.

Parker (2007) recognized the importance of risk development by considering the saying "garbage in, garbage out" (p. 1), and provided insight into the construction of quality risks by breaking them down into four *logic thread* components: title, statement, context, and closure criterion. The development flow starts with the context statement, moves to the risk statement, closure criteria, and title. Developing the closure criteria before the title seems out of order, but Parker (2007) noted this ensures the risk treatment strategy alleviates the risk statement's concern.

Parker (2007) gives three risk statement examples, including *If [state the concern], then [state the consequence]*. This approach to writing the risk statement can provide consistency with later risk calculations since the *if* statement represents the issue being assigned a probability of occurrence, while the *then* statement represents the consequence. Parker (2007) also discussed that individual risks need owners and champions to provide accountability and responsibility, communicate their importance, and ensure treatment activities are completed.

Table 4.11 shows a straightforward method to combine the praxis framework with a risk development process. The table provides base-level information that project teams may build-out with additional details. The first column of the table is the *Prioritized Activity List*, which is the output from the praxis framework. According to table 4.10, the first two activities from the case study that would be populated here, if removing the first and last activities, would be *1to2* and *7to9*. The second column, *Risk Identifier*, is a unique risk identifier developed for each priority activity. These risks could be developed using recommendations by Parker (2007) or another method. The next three columns represent the *Probability Value*, I*mpact Value*, and *Risk Score*, respectively. The tables list all these values between 0.00 and 0.99. While this can be true, the impact value can be represented in different ways (e.g., dollars), which would change the magnitudes and units of the impact and risk score values. The remaining columns of *Risk Closure Criteria*, *Risk Treatment*, *Risk Owner*, and *Risk Open/Closed* are additional details that should be developed, tracked, and managed to facilitate quality risk assessments.

Table 4.11. Risk analysis table incorporating the praxis framework. The Risk Identifier column links this table to the individually developed risks.

Priority Activity List	Risk Identifier	Probability Value (0.0 - 0.99)	Impact Value (0.0 - 0.99)	Risk Score (Probability x Impact)	Risk Closure Criteria	Risk Treatment	Risk Owner (Name)	Risk Open/ Closed
Priority Activity 1	Risk PA1/ ID1	0.00 - 0.99	0.00 - 0.99	Probability x Impact	Closure Criteria PA1/ID1	Risk Treatment PA1/ID1	Risk Owner PA1/ID1	Open/ Closed PA1/ID1
	Risk PA1/ ID2	0.00 - 0.99	0.00 - 0.99	Probability x Impact	Closure Criteria PA1/ID2	Risk Treatment PA1/ID2	Risk Owner PA1/ID2	Open/ Closed PA1/ID2
Priority Activity 2	Risk PA2/ ID1	0.00 - 0.99	0.00 - 0.99	Probability x Impact	Closure Criteria PA2/ID1	Risk Treatment PA2/ID1	Risk Owner PA2/ID1	Open/ Closed PA2/ID1
	Risk PA2/ ID2	0.00 - 0.99	0.00 - 0.99	Probability x Impact	Closure Criteria PA2/ID2	Risk Treatment PA2/ID2	Risk Owner PA2/ID2	Open/ Closed PA2/ID2

4.5 Problem & Thesis Statements

The problem and thesis statements are below, respectively. The praxis framework (i.e., decision-support process) calculated Activity Delay Risk and used it to quantify and prioritize activities for risk and opportunity analysis. Section 4.6 (Research Objectives, Questions, & Hypotheses) will explore how the framework relates to the research objectives, questions, and hypotheses.

Problem statement: *The failure to properly consider and quantify uncertainty early in the project management process results in too many late, overbudget, not fully successful, and/or failed projects.*

Thesis statement: *A structured methodology integrated with a consistent decision-support evaluation tool will effectively assess uncertainty and reduce the number of late, overbudget, not fully successful, and/or failed projects*

The problem and thesis statements discuss uncertainty, but not ambiguity. The praxis definitions of these terms were defined in Chapter 2 (Literature Review) and are taken from Lévárdy and Browning (2009). Ambiguity and uncertainty describe *not knowing what you don't know* and *knowing what you don't know,* respectively. These definitions provide a few important distinctions for the praxis framework:

1. The definitions of ambiguity and uncertainty are not standardized, so how the framework interacts with them will vary based on a practitioner's definitions.
2. Following the praxis definitions, an uncertain event is easier to quantify than an ambiguous event since it is known to possibly occur, and an ambiguous event will require retrospective analysis since its occurrence is completely unknown. This

concludes that the praxis framework's quantitative analysis surrounds the idea of risk prioritization that is focused on reducing uncertainty.

3. A project schedule is not entirely predictable if project uncertainty is fully identified since ambiguity may still exist. Recognizing this characteristic is the basis for why the praxis defined and contrasted ambiguity with uncertainty.
4. While the praxis framework may not directly reduce ambiguity, the quantitative analysis and risk prioritization of uncertainty could lead to an indirect reduction of ambiguity. This statement is difficult to prove since it requires quantification of an event that a practitioner does not know can occur; however, it is reasonable to postulate that the planning surrounding uncertainty could affect project ambiguity.
5. Looking forward, organizations may reduce ambiguity over time through detailed project tracking and categorization of risk register events as *ambiguity* or *uncertainty*. These events may transfer from the ambiguity category to the uncertainty category in future projects if the historical data is representative of the project types being pursued. This views the ambiguity and uncertainty classifications as dynamic, and the recategorization could be applied in connection with this praxis framework.

4.6 Research Objectives, Questions, & Hypotheses

The research objectives, questions, and hypotheses are paired together in subsections, and their conclusions are discussed below. While not discussed in each subsection, the conclusion regarding ambiguity and uncertainty from Section 4.5 (Problem & Thesis Statements) applies to the research objectives, questions, and hypotheses.

4.6.1 Research Objective, Question, & Hypothesis 1

Below are the first research objective, question, and hypothesis, respectively.

Research Objective 1: Develop a methodology that incorporates Decision-Making Under Deep Uncertainty (DMDU) for evaluating uncertainty early in the project management process.

Research Question 1: How can DMDU methods (e.g., Dynamic Adaptive Policy Pathways) be applied early in the project management process to quantify project uncertainty?

Hypothesis 1: The DMDU methodology can successfully be applied to a project network analysis to quantify project uncertainty.

While statistical methods provide insight into project duration performance, the initial duration estimates are often provided by subject matter experts. This means these foundational estimates that form a statistical analysis may themselves be uncertain. A suite of DMDU techniques were investigated to provide additional analysis tools for projects with this deep uncertainty. The praxis framework took inspiration from these techniques, including Dynamic Adaptive Policy Pathways, to build and display completion pathway possibilities and develop Activity Probabilities, Delay Impacts, and Activity Delay Risks. This type of *deterministic* approach focuses on all the network diagram's pathways to build *completion stories,* recognizing any completion pathway could become the critical path and providing a holistic approach to activity and network path-level risk and opportunity management.

4.6.2 Research Objective, Question, & Hypothesis 2

Below are the second research objective, question, and hypothesis, respectively.

Research Objective 2: Use statistical analysis methods to complement the DMDU methodology; integrate the statistical analysis with the DMDU methodology to provide greater resolution into project uncertainty.

Research Question 2: How can a task- and project-level statistical analysis (e.g., PERT and Monte Carlo) be incorporated with DMDU methods to determine project uncertainty?

Hypothesis 2: A statistical analysis can be integrated with the DMDU methodology to quantify project uncertainty.

Two different statistical methods (PERT and triangular distribution) modeled activity durations. In both cases, the activity duration attributes of expected value, standard deviation, and variance were combined, and a Normal distribution applied to the total project duration. A third statistical approach, Monte Carlo simulation, gave practitioners another option for statistical analysis. The activity expected values from the PERT statistical analysis were passed as input into the deterministic analysis, which are shown in table 4.2. While based on the selected distribution and parameters, the statistical analysis provides *bookends* for what can be expected regarding activity and project-level completion times. The deterministic analysis durations come from the statistical analysis and provide resolution to the data presented from the statistical analysis (i.e., it provides the *stories* that fit within the statistical analysis *bookends*). A major change to one analysis (i.e., new statistical parameters or moving to a different completion path) may result in needing to update the framework and calculate new risk and opportunity prioritization results.

4.6.3 Research Objective, Question, & Hypothesis 3

Below are the third research objective, question, and hypothesis, respectively.

Research Objective 3: Develop a decision-support tool that allows for evaluation of the DMDU methodology and perform simulations on project network diagrams; analyze and document the results.

Research Question 3: How can a decision-support tool be informed by DMDU methods and correlate project risk and opportunity recommendations?

Hypothesis 3: The DMDU and statistical methodologies can be linked with a decision-support tool to prioritize project activities that feed an activity-level risk and opportunity analysis.

A proof-of-concept computational tool for the framework was developed in Microsoft Excel. Separate worksheet tabs performed statistical and deterministic analyses, respectively. Another worksheet tab performed deterministic model validation using an alternate slack time calculation. A final worksheet tab summarized the information, including a prioritized list of activities based on the risk & opportunity score. This list could be moved forward to a risk and opportunity analysis, using risk management methods selected by the practitioner. The input and output information from the model were presented in chapters 3 and 4, respectively.

Chapter 5: Discussion & Conclusion

5.1 Introduction

This chapter provides the praxis industry contributions and opportunities for future research. The goals of the praxis were the development and testing of a framework to evaluate and prioritize risk and uncertainty activities early in the project management process. The work represents an incremental improvement that project and engineering managers may find useful, and it creates opportunities for discovery and future research regarding the application of the framework and associated methods.

5.2 Industry Contributions

The praxis framework fulfilled its research objectives. It took inspiration from Decision-Making under Deep Uncertainty (DMDU) methods to reimagine network diagrams, coupled the DMDU analysis with a statistical analysis to provide schedule bookends, and developed a proof-of-concept computational tool to facilitate the analysis. The framework provides a path to analyze project activity schedule information and inform risk and opportunity management; the framework is shown in figure 5.1.

In addition to the research objectives, the praxis framework contributes to the practical applications of project and engineering management in several areas including:

1. The framework results are quantitative activity prioritization estimates that a practitioner can use in conjunction with project information to prioritize risk management activities. This is especially helpful in cases where project schedule and budget limitations exist.

2. The pathway maps recognize that the initially identified critical path may change, and evaluating a suite of completion pathways broadens the analysis, providing a more holistic approach to project schedule management.
3. The holistic approach identified in item #2 defines important activity-level decision points, recognizing that a project's completion pathway is uncertain and decisions surrounding some activities may be more consequential than others.

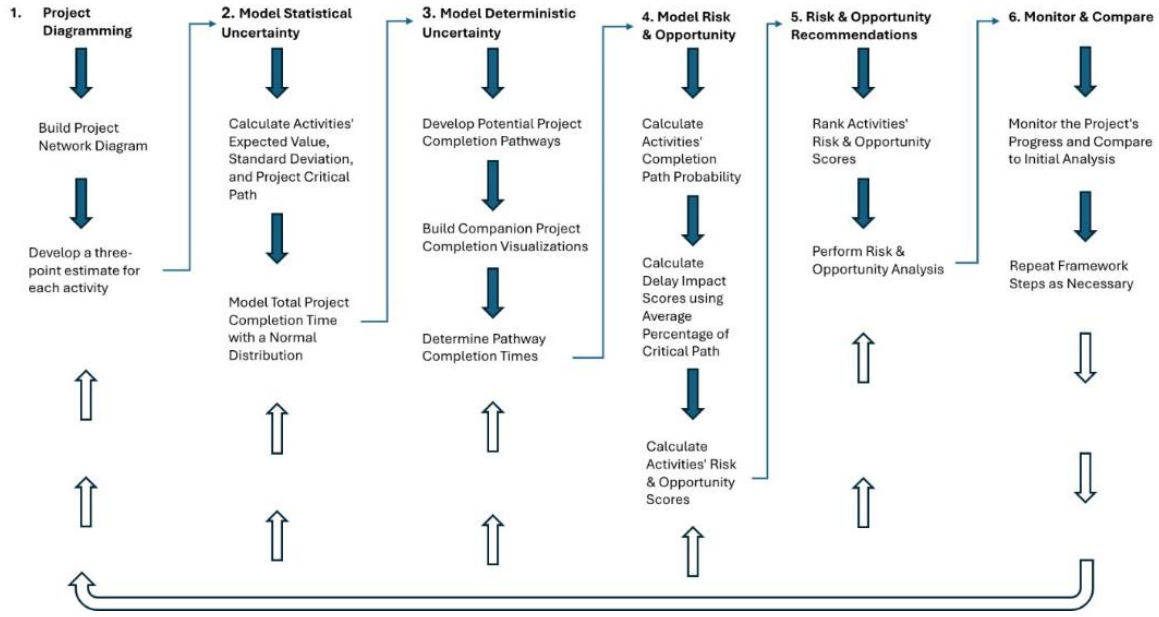

Figure 5.1. Praxis framework visual summary.

5.3 Future Research

Future research could help improve the praxis framework in several areas including:

1. **Additional Validation:** The praxis methodology for slack time was compared to an alternate methodology that adjusted the calculation from via network path to via activity. The two methods yielded similar results, but additional analysis to determine which slack time method is more effective for what network diagram

conditions could add insight into when to use the original praxis methodology versus taking the steps to calculate slack time by activity.

2. **Sensitivity Analysis:** A sensitivity analysis studying the effects of activity number, activity connections, and network pathways on Activity Delay Risk could provide context regarding the type(s) of network diagrams best suited for the framework. Network diagrams that lack complexity may yield Activity Probabilities and/or Delay Impacts that are uniform or similar in magnitude. This could reduce the value of the analysis. The network diagram evaluated in this praxis had nine network paths and activity interconnectedness, which could better suit the praxis framework due to the inherited diversity of the calculated results.
3. **Project Type Framework Testing:** The praxis framework was designed to be applied to any project network diagram, but the architecture of network diagrams vary. This variation could affect the framework's uncertainty management performance, and framework testing on different project classes and network diagram types may yield data on when its use is most justified. A comparison of with and without use of the framework project performance metrics could provide empirical data to validate its effectiveness, as mentioned in Section 1.8 (Research Limitations). This data collection could occur through surveys, be organized through an entity's project management office, and/or via another method. The data collection would require time since projects need to be completed, and an iterative process is recommended to take advantage of more data and any framework adjustments that better match an entity's project performance goals.

4. **Framework Expansion:** There are opportunities to expand the praxis framework in terms of software and analysis. This praxis provided a proof-of-concept tool that could be automated in Excel or other software. Artificial intelligence provides automation and data analysis opportunities. This praxis focused on a project network diagram for its analysis, but there may be opportunities to use other artifacts, such as a Work Breakdown Structure, to build similar prioritization tables for use in risk and opportunity management. This could complement or be performed in lieu of the praxis framework network diagram analysis.
5. **Expand DMDU in Engineering/Project Management:** This praxis framework took inspiration from the DMDU class of methodologies, primarily Dynamic Adaptive Policy Pathways. The problems in engineering and project management often experience deep uncertainty, so developing a framework that takes advantage of DMDU and its ability to treat uncertainty is justified. This praxis adds to a limited collection of engineering and project management DMDU literature, all of which provides a foundation for future work focused on improving project schedule uncertainty management.

Bibliography

Andretta, M. (2014). Some Considerations on the Definition of Risk Based on Concepts of Systems Theory and Probability. *Risk Analysis, 34*(7), 1184–1195.

Arashpour, M., Abbasi, B., Arashpour, M., Hosseini, M.R., and Yang, R. (2017). Integrated Management of On-Site Coordination and Off-Site Uncertainty: Theorizing Risk Analysis Within a Hybrid Project Setting. *International Journal of Project Management,* 35(4), 647-655.

Arashpour, M., Wakefield, R., Lee, E.W.M., Chan, R., and Hosseini, M.R. (2016) Analysis of Interacting Uncertainties in On-site and Off-site Activities: Implications for Hybrid Constuction. *International Journal of Project Management,* 34(7), 1393-1402.

Assaad, R., El-Adaway, I.H., and Abotaleb, I.S. (2020). Predicting Project Performance in the Construction Industry. *Journal of Construction Engineering and Management,* 146(5), 1-22.

Aven, T. (2013). On How to Deal with Deep Uncertainties in a Risk Assessment and Management Context, *Risk Analysis,* 33(12), 2082-2091.

Ben-Haim, Y. (2024). Evidence and Uncertainty: An Info-Gap Analysis of Uncertainty-Augmenting Evidence. *Risk Analysis,* 44(11), 2649-2659.

Ben-Haim, Y. and Laufer, A. (1998). Robust Reliability of Projects with Activity-Duration Uncertainty. *Journal of Construction Engineering and Management,* 12(2), 125-132.

Böhle, F., Heidling, E., and Schoper, Y. (2016) A New Orientation to Deal with Uncertainty in Projects. *International Journal of Project Management,* 34(7), 1384-1392.

Bowman, R.A. (2007). Efficient Sensitivity Analysis of PERT Network Performance Measures to Significant Changes in Activity Time Parameters. *Journal of Operational Research Society*, 58(10), 1354-1360.

Browning, T.R. (2019). Planning, Tracking, and Reducing a Complex Project's Value at Risk. *Project Management Journal,* 50(1), 71-85.

Browning, T.R. and Eppinger, S.D. (2002). Modeling Impacts of Process Architecture on Cost and Schedule Risk in Product Development. *IEEE Transactions on Engineering Management,* 49(4), 428-442.

Cates, G.R. and Mollaghasemi, M. (2007). The Project Assessment by Simulation Technique. *Engineering Management Journal*, 19(4), 3-10.

Chang, A.S. and Chiu, S.-H. (2005). Nature of Engineering Consulting Projects. *Journal of Management in Engineering,* 21(4), 179-188.

Chapman, C. (1997). Project Risk Analysis and Management-PRAM the Generic Process. *International Journal of Project Management, 15*(5), 273–281.

Cho, J-G. and Yum, B-J. (2004). Functional Estimation of Activity Criticality Indices and Sensitivity Analysis of Expected Project Completion Time. *Journal of Operational Research Society*, 55(8), 850-859.

Clark, C.E. (1962). Letter to the Editor – The PERT Model for the Distribution of an Activity Time. *Operations Research*, 10(3), 405-406.

Cox, L.A.(T). (2008). What's Wrong with Risk Matrices?. *Risk Analysis*, 28(2), 497-512.

Cox, L.A.(T). (2012). Confronting Deep Uncertainties in Risk Analysis. *Risk Analysis,* 32(10), 1607-1629.

De Meyer, A., Loch, C.H., and Pich, M.T. (2002). Managing Project Uncertainty: From Variation to Chaos. *MIT Sloan Management Review*, Winter (2002), 60-67.

Deshmukh, P. and Rajhans, N. (2018). Comparison of Project Schedule Techniques: PERT versus Monte Carlo Simulation. *Industrial Engineering Journal*, 11(7), 1-13.

Garvey, P.R., Book, S.A., and Covert, R.P. (2016). *Probability Methods for Cost Uncertainty Analysis A Systems Engineering Perspective* (2nd ed.). CRC Press, an imprint of Taylor & Francis Group, an Informa business.

Gomes, L.A.D.V., Brasil, V.C., Paula, R.A.S.R.D., Facin, A.L.F., Gomes, F.C.D.V, and Salerno, M.S. (2019). Proposing a Multilevel Approach for the Management of Uncertainties in Exploratory Projects. *Project Management Journal,* 50(5), 554-570.

Gomes, L.A.D.V., Lopez-Vega, H., and Facin, A.L.F. (2021). Playing Chess or Playing Poker? Assessment of Uncertainty Propagation in Open Innovation Projects. *International Journal of Project Management,* 39(2), 154-169.

Grant, K.P. and Pennypacker, J.S. (2006). Project Management Maturity: An Assessment of Project Management Capabilities Among and Between Selected Industries. I*EEE Transactions on Engineering Management*, 53(1), 59-68.

Groves, D.G., Bloom, E., Lempert, R.J., Fischback, J.R., Nevills, J., and Goshi, B. (2015). Developing Key Indicators for Adaptive Water Planning. *Journal of Water Resources Planning and Management,* 14(7), 05014008-1-05014008-10

Haimes, Y.Y. (2009). On the Complex Definition of Risk: A Systems-Based Approach. *Risk Analysis,* 29(12), 1647-1654.

Hall, J.W., Lempert, R.J., Keller, K., Hackbarth, A., Mifere, C., and McInerney, D.J. (2012). Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods. *Risk Analysis,* 32(10), 1657-1672.

Hoffman, G.J., Thal Jr., A.E., Webb, T.S., Weir, J.D. (2007). Estimating Performance Time for Construction Projects. *Journal of Management in Engineering,* 23(4), 193-199.

Hubbard, D.W. (2020). The Failure of Risk Management, 2nd Edition. John Wiley & Sons, Inc.

Jensen, C., Johansson, S., and Löfström, M. (2006). Project Relationships – A Model for Analyzing Interactional Uncertainty. *International Journal of Project Management,* 24(1), 4-12.

Jiang, J. J., Klein, G., and Ellis, T.S. (2002). A Measure of Software Development Risk. *Project Management Journal, 33*(3), 30–41.

Kaplan, S. (1997). The Words of Risk Analysis. *Risk Analysis,* 17(4), 407-417.

Kaplan, S. and Garrick, B. J. (1981). On The Quantitative Definition of Risk. *Risk Analysis*, *1*(1), 11–17.

Khodakarami, V., Fenton, N., and Neil, M. (2007). Project Scheduling: Improved Approach to Incorporate Uncertainty Using Bayesian Networks. P*roject Management Journal,* 38(2), 39-49.

Kolltveit, B. J., Karlsen, J.T., and Grønhaug, K. (2004). Exploiting Opportunities in Uncertainty During the Early Project Phase. *Journal of Management in Engineering,* 20(4), 134-140.

Kou, Y. and Lu, S. (2013). Using Fuzzy Multiple Criteria Decision Making Approach to Enhance Risk Assessment for Metropolitan Construction Projects. *International Journal of Project Management*, 31(4), 602-614.

Kvalnes, Ø. (2016). Living with the Unknown Unknown: Uncertainty in Projects. *Project Management Journal,* 47(3), 101-108.

Kwakkel, J.H., Haasnoot, M., and Walker, W.E. (2016). Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for Model-Based Decision Support under Deep Uncertainty. *Environmental Modelling & Software,* 86(2016), 168-183.

Kwakkel, J.H., Walker, W.E., and Haasnoot, M. (2016). Coping with the Wickedness of Public Policy Problems: Approaches for Decision Making under Deep Uncertainty [Editorial]. *Journal of Water Resources Planning and Management,* 142(3), 01816001-1-01816001-5.

Lechler, T.G., Edington, B.H., and Gao, T. Challenging Classic Project Management: Turning Project Uncertainties into Business Opportunities. *Project Management Journal,* 43(6), 59-69.

Lechler, T.G., Ronen, B., and Stohr, E.A. (2005). Critical Chain: A New Project Management Paradigm or Old Wine in New Bottles?. *Engineering Management Journal,* 17(4), 45-58.

Lempert, R.J. and Turner, S. (2021). Engaging Multiple Worldviews with Quantitative Decision Support: A Robust Decision-Making Demonstration using the Lake Model. *Risk Analysis,* 41(6), 845-865.

Lévárdy, V. and Browning, T.R. (2009). An Adaptive Process Model to Support Product Development Project Management. *IEEE Transactions on Engineering Management,* 56(4), 600-620.

Maes, T., Gebhardt, K., Riel, A. (2022). The Relationship Between Uncertainty and Task Execution Strategies in Project Management. *Project Management Journal,* 53(4), 382-396.

Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M, and Popper, S.W. (2019). Chapter 1 Introduction. In V.A.W.J. Marchau, W.E. Walker, P.J.T.M. Bloemen, and S.W. Popper (Eds.), *Decision Making under Deep Uncertainty From Theory to Practice* (pp. 1-20). The Society for Decision Making under Deep Uncertainty.

Marzi, G., Ciampi, F., Dalli, D., and Dabic, M. (2021). New Product Development During the Last Ten Years: The Ongoing Debate and Future Avenues. *IEEE Transactions on Engineering Management,* 68(1), 330-344.

McLain, D. (2009). Quantifying Project Characteristics Related to Uncertainty. *Project Management Journal,* 40(4), 60-73.

Min, Y. and Shou-rong, L. (2013) Influence of Behavioral Factors on Project Schedule Management: a Monto Carlo Method. *25th Chinese Control and Decision Conference (CCDC)*, 4831-4835.

Mokhtari, H., Kazemzadeh, R.B., and Salmasnia, A. (2011). Time-Cost Tradeoff Analysis in Project Management: An Ant System Approach. *IEEE Transactions on Engineering Management,* 58(1), 36-43.

Ortiz de Orue, D.A., Taylor, J.E., Chanmeka, A., and Weerasooriya, R. Robust Project Network Design. *Project Management Journal,* 40(2), 81-93.

Parker, V. (2007). Taking Out the Garbage – How to Get Good Risks into Your Risk Tool. *INCOSE International Symposium*, 17(1), 1112-1122.

Petronijevic, J., Etienne, A., Bassetto, S., and Siadat, A. (2023) The Missing Link Between Project and Product Risk Management: From the Review to the Call to Action. *Journal of Engineering and Technology Management,* 69(2023), 101770.

Pinto, J.K. (2020). *Project Management Achieving Competitive Advantage* (5th ed., Global ed.). Pearson Education Limited.

Pollack-Johnson, B. and Liberatore, M.J. (2005). Project Planning Under Uncertainty Using Scenario Analysis. *Project Management Journal,* 36(1), 15-26.

Project Management Institute. (2021). *A Guide to the Project Management Body of Knowledge PMBOK Guide Seventh Edition and The Standard for Project Management.* Project Management Institute.

Pulat, P.S. and Horn, S.J. (1996) Time-Resource Tradeoff Problem. *IEEE Transactions on Engineering Management,* 43(4), 411-417.

Qazi, A., Daghfous, A. and Khan, M.S. (2021). Impact of Risk Attitude on Risk, Opportunity, and Performance Assessment of Construction Projects. *Project Management Journal, 52*(2), 192–209.

Qazi, A., Dikmen, I., and Birgonul, M. T. (2020). Mapping Uncertainty for Risk and Opportunity Assessment in Projects. *Engineering Management Journal*, 32(2), 86-97.

Qazi, A., Quigley, J., Dickson, A., and Kirytopoulos, K. (2016). Project Complexity and Risk Management (ProCRiM) Towards Modelling Project Complexity Driven Risk Paths in Construction Projects. *International Journal of Project Management,* 34(7), 1183-1198.

RAND Corporation (n.d.). Decision Making Under Deep Uncertainty. Retrieved February 2025 from https://www.rand.org/global-and-emerging-risks/centers/methods-centers/pardee/dmdu-decision-making-under-deep-uncertainty.html

Reis, J. and Shortridge, J. (2020). Impact of Uncertainty Parameter Distribution on Robust Decision Making Outcomes for Climate Change Adaptation under Deep Uncertainty. *Risk Analysis,* 40(3), 494-511.

Regev, S., Shtub, A., and Ben-Haim, Y. (2006). Managing Project Risks as Knowledge Gaps. *Project Management Journal, 37*(5), 17–25.

Sadeghi, N., Dehghani, M.S., Ingolfsson, A. (2024). Choice of Probability Distributions for Activity Durations in Project Networks with Limited Sample Size. *Journal of Construction Engineering and Management,* 150(3), 04024002-1-04024002-15.

Salas-Morera, L., Arauzo-Azofra, A., García-Hernández, L., Palomo-Romero, J.M., and Ayuso-Muñoz, J.L. (2018). New Approach to the Distribution of Project Completion Time in PERT Networks. *Journal of Construction Engineering and Management,* 144(10), 04018094-1-04018094-12.

Sanchez-Cazorla, A., Alfalla-Luque, R., and Irimia-Dieguez, A.I. (2016). Risk Identification in Megaprojects as a Crucial Phase of Risk Management: A Literature Review. *Project Management Journal,* 47(6), 75-93.

Saunders, F.C., Gale, A.W., and Sherry, A.H. (2015). Conceptualising Uncertainty in Safety-Critical Projects: A Practitioner Perspective. *International Journal of Project Management,* 33(2), 467-478.

Saunders, F.C., Gale, A.W., and Sherry, A.H. (2016). Mapping the Multi-Faceted: Determinants of Uncertainty in Safety-Critical Projects. *International Journal of Project Management,* 34(6), 1057-1070.

Schrader, S., Riggs, W.M., Smith, R.P. (1993). Choice Over Uncertainty and Ambiguity in Technical Problem Solving. *Journal of Engineering and Technology Management,* 10(1-2), 73-99.

Shipley, M.F., de Korvin, A., and Omer, K. (1997). BIFPET methodology versus PERT in Project Management: Fuzzy Probability Instead of the Beta Distribution. *Journal of Engineering and Technology Management,* 14(1), 49-65.

Sjödin, D. R., Frishammar, J., and Eriksson, P.E. (2016). Managing Uncertainty and Equivocality in Joint Process Development Projects. *Journal of Engineering and Technology Management,* 39(2016), 13-25.

Tahan, M. and Ben-Asher, J.Z. (2005). Modeling and Analysis of Integration Processes for Engineering Systems. *Systems Engineering,* 8(1), 62-77.

Thamhain, H. (2013). Managing Risks in Complex Projects. *Project Management Journal, 44*(2), 20–35.

Van Slyke, R. (1963). Letter to the Editor – Monto Carlo Methods and the PERT Problem. *Operations Research*, 11(5), 839-860.

Van Slyke, R. (1963). Uses of Monte Carlo in PERT. https://www.rand.org/pubs/research_memoranda/RM3367.html

Walker, D.H.T., Davis, P.R., and Stevenson, A. (2017). Coping with Uncertainty and Ambiguity Through Team Collaboration in Infrastructure Projects. *International Journal of Project Management,* 35(2), 180-190.

Ward, S. and Chapman, C. (2003). Transforming Project Risk Management into Project Uncertainty Management. *International Journal of Project Management,* 21(2), 97-105.

Wied, M., Koch-Ørvad, N., Welo, T., and Oehmen, J. (2020). Managing Exploratory Projects: A Repertoire of Approaches and their Shared Underpinnings. *International Journal of Project Management,* 38(2), 75-84.

Wiewiora, A.M. and O'Connor, P.J. (2022). Not all Project Ambiguity is Equal: A Typology of Project Ambiguity and Implications for its Management. *International Journal of Project Management,* 40(8), 921-933.

Williams, T. (2017). The Nature of Risk in Complex Projects. *Project Management Journal,* 48(4), 55-66.

Williams, T. and Samset, K. (2010). Issues in Front-End Decision Making on Projects. *Project Management Journal,* 41(2), 38-49.

Xue, R., Baron, C., Vingerhoeds, R., and Esteban, P. (2022). Enhancing Engineering Project Management Through Process Alignment. *Engineering Management Journal,* 34(2), 230-248.

Yang, Q., Lu, T., Yao, B., and Zhang, B. (2014). The Impact of Uncertainty and Ambiguity Related to Iteration and Overlapping on Schedule of Product Development Projects. *International Journal of Project Management,* 32 (5), 827-837.

Yim, R., Castaneda, J., Doolen, T., Tumer, I., and Malak, R. (2015). A Study of the Impact of Project Classification on Project Risk Indicators. *International Journal of Project Management, 33*(4), 863–876.

Zhang, H. (2011). Two Schools of Risk Analysis: A Review of Past Research on Project Risk. *Project Management Journal,* 42(4) 5-18.

Zhang, X., Goh, M., Bai, S., Wang, Z., and Wang, Q. (2024). Project Risk Response Decision Making Under Uncertain Project Interdependencies. *IEEE Transactions on Engineering Management,* 71, 7364-7378.

Zheng, X., Lu, Y., and Chang, R. (2019). Governing Behavioral Relationships in Megaprojects: Examining Effects of Three Governance Mechanisms under Project Uncertainties. *Journal of Management in Engineering,* 35(5), 04019016-1-04019016-16.

Zhong, Y., Chen, Z., Zhou, Z., and Hu, H. (2018). Uncertainty Analysis and Resource Allocation in Construction Project Management. *Engineering Management Journal*, 30(4), 293-305.

Appendix A: Permissions

8/10/25, 6:44 PM The George Washington University Mail Re: Permission Request (Van Slyke, 1963)

GW

Travis Yonts [redacted]

Re: Permission Request (Van Slyke, 1963)
2 messages

[redacted] Tue, Mar 11, 2025 at 1:17 PM
To: Travis Yonts [redacted]

Hi, Travis,

Thanks for reaching out. This request is granted. RAND considers this fair use. Please do be sure to include the appropriate citation as well as "adapted from" in your source lines.

Thank you for your interest in RAND. We're glad you find the research useful.

Best regards,

[redacted]

[redacted]

From: Travis Yonts [redacted]
Date: Thursday, February 20, 2025 at 5:37 AM
To: permissions <permissions@rand.org>
Subject: [EXT] Permission Request (Van Slyke, 1963)

[redacted] 1/2

Hello RAND Copyright Clearance Center,

I am a graduate student in engineering management at The George Washington University. My research project is developing a methodology to evaluate uncertainty early in the project management process. I came across a report by Van Slyke (1963) during my literature review. This report provides a good example of an early statistical comparison between the Program Evaluation and Review Technique and Monte Carlo Simulation.

I am requesting permission to use an adaptation of Figure 1 (Appendix, page 18) from that report in my praxis research paper. I plan to use the attributes of the figure to test my praxis methodology. I also request permission to use adaptations of figures 2 (page 19), 3 (page 20), and 4 (page 22) for comparative purposes.

The report can be found on the RAND website here and a citation is provided below.

Van Slyke, Richard, Uses of Monte Carlo in PERT. Santa Monica, CA: RAND Corporation, 1963. https://www.rand.org/pubs/research_memoranda/RM3367.html.

Please let me know if you have questions or concerns, and thank you for considering my request.

Travis D. Yonts

[redacted]

This email message is for the sole use of the intended recipient(s) and may contain information that is sensitive, proprietary, and/or privileged. Any unauthorized review, use, disclosure or distribution is prohibited. If you are not the intended recipient, please contact the sender by reply email and destroy all copies of the original message.

Travis Yonts [redacted] Fri, Mar 14, 2025 at 8:31 AM

Hi [redacted],

I appreciate the response and approval. I will include citations and "adapted from" text.

Thank you,

Travis D. Yonts

[redacted]

[Quoted text hidden]

[redacted] 2/2