Modeling technical decision-making for product development in engineering organizations

A thesis submitted in fulfillment
of the requirements for the degree of
Doctor of Philosophy

By

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March 2024

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Declaration

I, Muhammad Fahmi Ibrahim, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Date: 6th March 2024

Abstract

Decision-making is a fundamental practice in engineering organizations that significantly influences the value of the products developed. However, despite the expectation that highly technical and safety-critical decisions should follow a rational process, human behavior often interferes, resulting in outcomes that are less than entirely rational. This research aims to model the interplay between rational and behavioral components in technical decision-making during product development. A Unified Model of Rational and Behavioral Technical Decision-Making (UMRBTDM) was developed as the conceptual framework for this study. A mixed-methods strategy was employed, consisting of in-depth interviews with 15 participants to explore their behavior and organizational technical decision-making process for the qualitative component, and the development of questionnaires to assess decision-making tendencies using realistic scenarios, garnering 96 responses for the quantitative component.

The Synthesized Model of Technical Decision-Making in Product Development, which was later developed by refining the UMRBTDM based on the research data, models the interaction between rational analysis and biases in the technical decision-making process. Data analysis showed that technical decision-making in engineering organizations resembles a three-way tug of war where rule-following, rational analysis, and personal judgment pull in different directions to reach an equilibrium. The decision-makers were also found to be moderately biased and more prone to social bias than cognitive bias. Social and cognitive biases have also been shown to be embedded in the processes, and removing biases from the equation is impractical. These biases do not necessarily lead to bad decision-making because they are sometimes used to mitigate the limitations of rational analysis. Rational analysis is a powerful tool that should be pursued but at the same time, behavioral elements should be allowed to co-exist in the decision-making process, as long as engineering organizations can identify and manage the negative side effects of heuristics and biases in the decision-making process.

Impact Statement

The research presented in this thesis on technical decision-making in safety-critical, highly complex systems industries offers significant implications both within and outside the academic sphere. By modeling the dynamic interplay between rational and behavioral components in technical decision-making, this research broadens the understanding of the technical decision-making process and offers insights that could be instrumental in refining research methods in these fields and influencing organizational decision-making strategies.

The thesis proposes a synthesized model of rational and behavioral technical decision-making, specifically applicable to product development. This theoretical contribution enhances the understanding of how biases may impact decision analysis and provides a comprehensive framework for studying the technical decision-making process. The thesis also provides valuable insights into the decision-making process employed in engineering organizations for technical decisions. It lays out the current landscape of the technical decision-making process in engineering organizations, especially those in safety-critical industries, and analyzes the gaps and deviations between the expectation and reality of the decision-making process. This practical contribution aids organizations in understanding and evaluating their decision-making strategies and processes, enabling them to make informed improvements. Furthermore, this thesis further increases the academic community's understanding of biases within the technical decision-making process, which is also relevant to industry. This encourages decision-makers to critically examine their own organization’s susceptibility to bias during technical decision-making and implement strategies to mitigate its impact.

In conclusion, this thesis improves the academic understanding of technical decision-making and provides practical applications for refining decision-making processes in engineering organizations. It bridges the gap between theoretical models and practical realities, this research provides a robust framework for enhancing the efficacy of technical decision-making in various industries, particularly those that are safety critical.

Acknowledgment

In the name of God, the Merciful, the Compassionate. With His mercy, I had the opportunity to embark on my lifelong academic journey. With His compassion, I had enough strength to navigate through this journey until the end.

I would like to express my gratitude to my supervisor, Dr. Michael Emes, for his guidance throughout the journey. It was a very long roller-coaster ride of challenges and trials, but the end was always in sight.

To my wife, Raimi Shazni, I am deeply grateful for your unwavering support and understanding in my pursuit of a PhD. My impossible mission to work and study full-time caused so much pain and hardship, and I thank you for being there for me through thick and thin. I will not do a second PhD, I promise.

To my mother, Dr. Lailawati, thank you very much for being my inspiration to embark on this journey and your unrelenting and tireless effort to help me push through it. To my father, Hj. Ibrahim, thank you for all your sacrifices and encouragement for your children to achieve the highest academic level, and I dedicate this PhD to you.

I am thankful to God for bestowing me with two beautiful children during this long and difficult journey. To Hamza and Khayra, in your search for success and happiness, remember that you are never alone in this journey, nor will you be at its end. Your achievements are not just your own, but a shared joy with those around you.

And last and surely least, I acknowledge the use of Microsoft Word’s Grammar Checker, Grammarly, and OpenAI’s ChatGPT 4 to proofread my final draft.

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Definition of Terms

Normative model:

prescribes how people or organizations should behave to achieve optimal decisions (Rechtin & Maier, 2000; Simon, 1972).

Descriptive model:

explains how people actually behave when making decisions (French, Bell, Raiffa, & Tversky, 2006; Over, 2008).

Rational model:

describes the decision-maker as possessing a “well-organized and stable system of preferences and a skill in computation that enables him to calculate, for the alternative courses of action available to him, which of these will permit him to reach the highest attainable point on his preference scale” (Simon, 1955)

Behavioral (or boundedly-rational) model:

explains that due to inherent limitations in processing information and solving complex problems, individuals often seek to satisfy their minimum utility requirements instead of maximizing them (Simon, 1956).

Heuristics:

a mental shortcut, or rule-of-thumb, where people base decisions on their intuitions to make decisions quickly or to avoid the taxing information-processing requirements of the rational model (Hodgkinson & Starbuck, 2008; Robbins & Judge, 2001).

Bias:

an inclination or predisposition of the mind towards a particular viewpoint or outcome, which represents a deviation from the position that would be predicted by rational decision-making.

Judgement:

subjective assessment of probability, physical quantities or qualities (Kahneman & Tversky, 1974).

1 Introduction

Organizational decision-making processes have been largely supported by systematic and rational methods. Studies have shown that human factors in organizational settings influence the decision-making process, which can alter the intended outcome of the decision made (Carley & Frantz, 2009; Shapira, 2002). Thus, it is important to understand the influence of human factors on the systematic decision-making process in an organization.

1.1 Organizational Decision-Making

Decision-making in organizations is somewhat akin to day-to-day personal decision-making but with a few key differences. Organizations are structured entities, with different layers within the organizations, each responsible for different decisions. Senior management is responsible for long-term strategic decisions that will steer the direction of the organization. Middle managers interpret the decisions and plan tactical decisions, which are then implemented by junior managers into day-to-day operational decisions. Although decision theory scholars argue that optimum decisions can only be achieved with rational decision-making (Baron, 2008; March, 1978), they also agree that humans are inefficient information-processors (March, 1978). In order to increase rationality in organizational decision-making, organizations prescribe decision rules and the use of decision analysis tools (Dobbin, 1994; Krumm & Rolle, 1992). However, as long as humans participate in organizational decision-making processes, there will always be human factors that deviate the process from its rational goal.

The decision-maker's bias – one of the human factors – is a soft element in the decision-making process that can be captured by examining organizational behaviors. Organizational behaviors, which include group dynamics, play important roles in organizational decision-making (Forsyth, 1990). Group dynamics, which have elements of social bias such as groupthink, together with personality traits, for example, self-efficacy and risk-taking among different status and cultural groups, may influence the outcome of a decision (Aldag & Fuller, 1993; Harvey & Consalvi, 1960; Mau, 2000; Mullen & Copper, 1994). Different group dynamics can produce different decision outcomes despite having the same strategic decision at the outset. Therefore, it is crucial to identify and model these human factors into the decision-making process, so that the overall process of decision-making at the organizational level, which is mainly driven by rational methods, reflects the organic component of the decision-making process.

1.2 Problem Statement

Product development in engineering-based organizations is a technically-oriented process. Quantitative data are fed into the technical decision-making process to produce rationally-driven decision outputs. To ensure objectivity, engineering organizations, professional bodies, and industry trade associations have outlined detailed guidelines on the application of a systematic and rational decision-making process. In academia, countless decision support tools have also been proposed to ensure the rationality of technical decision-making. In doing so, what these scholars may have missed is the soft element in decision-making, human behavior. Humans are central to most organizational decision-making processes, including technical-related decisions. They are boundedly-rational creatures (Simon, 1957), whose preferences are ever-changing and inconsistent (March, 2002). Therefore, as long as humans make technical decisions, it begs the question of whether total rationality in the decision-making process can be achieved. Moreover, we should not assume that complete rationality is desirable in all decision-making cases. Human intuition is a highly developed, non-logical form of reasoning, based on experience and formal learning (Barnard, 1938). It cannot be dismissed as a non-optimal form of decision-making. Therefore, an examination of the influence of human behavior in decision-making may shed some light on the role of rationality in the technical decision-making process.

Based on the widespread practice that decisions should be centered around rational deliberation for an optimal outcome, organizational decision-making processes can be characterized as a decision based on rational choice or rule-following (March, 2002). Both decision-making characteristics are present in engineering organizations that develop technical products. However, rational choice is expected when making technical decisions in product development, particularly when the decision-making is supported by rational analysis.

Engineering organizations also exhibit rule-following behavior where conformance to product development process norms, defined in their respective industry or by international standards, is systematically applied. Rules and norms are generally created based on formal learning, past experiences, and conscious agreements between rule makers (March, 2002; Zhou, 2002). However, this behavioral component of rule-following characteristics is interlaced with its rational component. The rational component, on the other hand, can be observed in many product development standards and guidelines where rationality is required in the technical decision-making process (ISO/IEC 15288, 2005; NASA, 2007).

The development of technical products revolves around mathematical objectivity and measurable performance. Product design and development are often conducted based on rational analysis where calculations, simulations, and numerical analysis are institutionalized (Attia, Gratia, De Herde, & Hensen, 2012; C.-H. Chen, Donohue, Yücesan, & Lin, 2003; Mavris, Bandte, & DeLaurentis, 1999). Decision analysis, an example of rational analysis, has been widely used in industries involved in the technical decision-making process (Wright & Goodwin, 2009). Decision analysis tools, such as influence diagrams, Monte Carlo techniques, probabilistic forecasting, and decision tree, have been used in the industry to increase the effectiveness of engineering organizations' decision-making to varying degrees (Hess, 1993; Krumm & Rolle, 1992; Ulvila & Brown, 1982). Academic researchers have also proposed new decision analysis tools to be used during product development such as multiple variations of fuzzy logic (Büyüközkan & Feyzıoǧlu, 2004; Lin & Lee, 1991; Yan, Chen, & Shieh, 2006) and multi-attribute utility analysis (Büyüközkan & Ateş, 2007; Malak, Aughenbaugh, & Paredis, 2009). Thus, the expectation of rationality in technical decision-making is a norm in engineering organizations.

On the other hand, human behavior in organizational decision-making cannot be defined as rational (Simon, 1947). Heuristics and biases influence organizational decision-making processes and deviate decisions from their optimal outcomes. Overconfidence, anchoring, confirmation, and availability biases are common occurrences in organizational decision-making processes (Robbins & Judge, 2001). These biases have been proven to cause sub-optimal decisions, especially in the product development process in engineering organizations. For example, functional members within organizations, such as service, manufacturing, and research and development, can bias decision-making in the product development process due to internal conflicts to achieve a dominant position in the communication hierarchy (Antioco, Moenaert, & Lindgreen, 2008). In the space industry, there is also an inherent bias to downplay external risks, such as the political situation and contractual variability, that can impact the viability of space missions (Reeves, Eveleigh, Holzer, & Sarkani, 2013). Furthermore, Boulding, Morgan, and Staelin (1997) discovered that, due to escalation of commitment or sunk-cost fallacy, managers tend to prolong commitment to a failed new product.

As demonstrated in the discussion above and based on the author's professional experience in the industry, many technical decisions were treated with the decision-maker's subjective judgments, even when they have quantifiable information, measurable constraints, and objective requirements. Decision-makers, time and time again, fell into the trap of heuristics and biases due to reasons such as personal issues and political environment. It is an apparent problem in engineering organizations when decision-makers are not making technical decisions objectively, despite the need for rational analysis.

The expectation for rationality in technical decision-making is even more pronounced in safety-critical and highly-complex systems such as in the automotive, space, and medical device industries. Organizations in these industries are expected to conform to a higher standard of product development process due to the technical and specific nature of their products. Their highly complex products may consist of multiple interfacing systems which include electrical, mechanical, software, chemical, and biological systems. Moreover, the fallout of safety and health hazards of the products may have huge impacts not only for the direct users but for society in general. The dynamics between competitive pricing, high production volumes, and stringent regulations to ensure public safety compel automotive industry players to make technical decisions with due deliberation. On the other hand, medical device companies may not face the same constricting cost target, but high individual health risk requires a rigorous decision-making process during product development. Large capital expenditure coupled with high technical complexity in the space sector, albeit with low production volumes, requires space companies to adhere to tight regulations imposed by their stakeholders. Therefore, the technical decisions taken in these organizations must be finely-balanced between cost, safety and health hazards, technical complexity, project timing, manpower allocation, and legal requirements.

Due to these factors, these organizations exhibit rule-following behavior which contains both rational and behavioral decision-making components. The normative technical decision-making process in these industries is largely governed by rational analysis (ISO/IEC 15288, 2005). In the real-world, technical decisions are made by boundedly rational humans who do not necessarily conform to the rationality expected. This particular idiosyncrasy is the subject of this research interest.

1.3 Research Aims

Rational analysis is the governing principle for technical decision-making; however, human decision-makers incorporate behavioral elements into the process. With this curiosity in mind, this research seeks to understand the dynamic contrast between rational and behavioral elements in the technical decision-making process in product development in engineering organizations within safety-critical complex system industries. Therefore, the aims of this research are:

1. To investigate the behavioral components that influence technical decision-making.
2. To model the interaction between rational and behavioral components of technical decision-making in product development

1.4 Research Approach

Although technical decision-making is a subset of the broader field of decision-making, this research aims to investigate the underexplored aspect of behavioral elements within technical decision-making. Therefore, a systematic approach is essential to ensure a comprehensive exploration of all possible perspectives. The research approach involves exploring the decision-making field by methodically building up an understanding of the topic and subsequently narrowing it down to the specific area of interest, in this case, technical decision-making in engineering organizations.

Therefore, a *sequential exploratory strategy* was chosen for this research because of its layered approach that allowed for the exploration of the decision-making behavior in engineering organizations through qualitative research and was supported with quantitative analysis to verify the interpretation of the qualitative discoveries. The layered approach started with the literature review, as the preliminary analysis. It provided a groundwork to understand the historical and current research in decision-making topics, especially in engineering organizations. This was followed by a sequential exploratory mixed-method strategy. The exploratory qualitative phase used expert interviews and content analysis to explore the organizational decision-making landscape and build a model for further quantitative analysis. The exploratory phase used survey research and statistical analysis to quantify the issues identified through the qualitative phase and to test the model for further refinement. The detailed research design can be found in (Figure 25).

1.5 Scope

The scope of this thesis was confined to the modeling of technical decision-making process in product development in engineering organizations, with a focus on safety-critical, highly complex systems industries. The study analyzed the presence of biases in the decision-making process and incorporated the findings into a graphical form of a model. Data were collected via interviews and surveys from various employees who were directly involved in the technical decision-making process within different engineering organizations. The decision-making process was analyzed within the context of the design development phase of the product development process of these organizations.

Specifically, concept selection as a facet of technical decision-making was chosen as the decision context. Concept selection in architectural design represents one of many technical decision-making processes that exist within the whole spectrum of a product lifecycle. Since architectural design provides the design blueprints for product design teams (Haskins et al., 2006), a robust and rational decision-making process in selecting a viable concept is imperative. Hence, concept selection represents a critical juncture in the product development process of engineering-based organizations, as any negative repercussions of a sub-optimal concept selection process will resonate throughout the product development process due to the longitudinal nature of the process (Shapira, 2002).

1.6 Thesis Outline

The introductory chapter provides a brief explanation of the research in the thesis and defines the research aims and its scope. Chapter 2 highlights relevant literature by explaining the progress of decision theory research over the years and then narrows the focus of the literature review to the product development process in engineering organizations. Based on the literature review and guided by the research aims, a set of research questions was formulated, and each research question was assigned with research actions. Chapter 3 explains and justifies the research methodologies used while providing the conceptual framework that becomes the foundation of this thesis. The previously defined research actions guided the development of research instruments, which are described in this chapter. Chapter 4 is split into two distinctive but related areas. Sections 4.1 and 4.2 present the research results objectively, while Section 4.3 answers the sub-research questions by weaving evidence and data from the findings with the author's critical analysis and supported by existing literature. Finally, Chapter 5 concludes the thesis by answering the main research question and presenting the limitations of the research. A brief discussion of the possible directions of this topic can be found at the end of the chapter.

In order to steer the research toward the fulfillment of its goals and to ensure a systematic development of research instruments, research aims, questions, and actions were constructed to fulfill their specific roles. Research aims (Section 1.3) represent the primary goals of the research project and intended outcomes where two research aims were formulated based on the thesis title and problem statement. These aims were then decomposed into research questions (Section 2.7). Whereas research aims are the broad overarching goals of the research, research questions refine those aims into more objective and tangible expectations with each research question was then assigned with measurable research actions (Section 2.7). These actions were subsequently allocated to a specific research methodology (Section 3.2.2, Section 3.2.3) to guide the development of the research instruments. Figure 1 visualizes the decomposition of research aims to research actions.

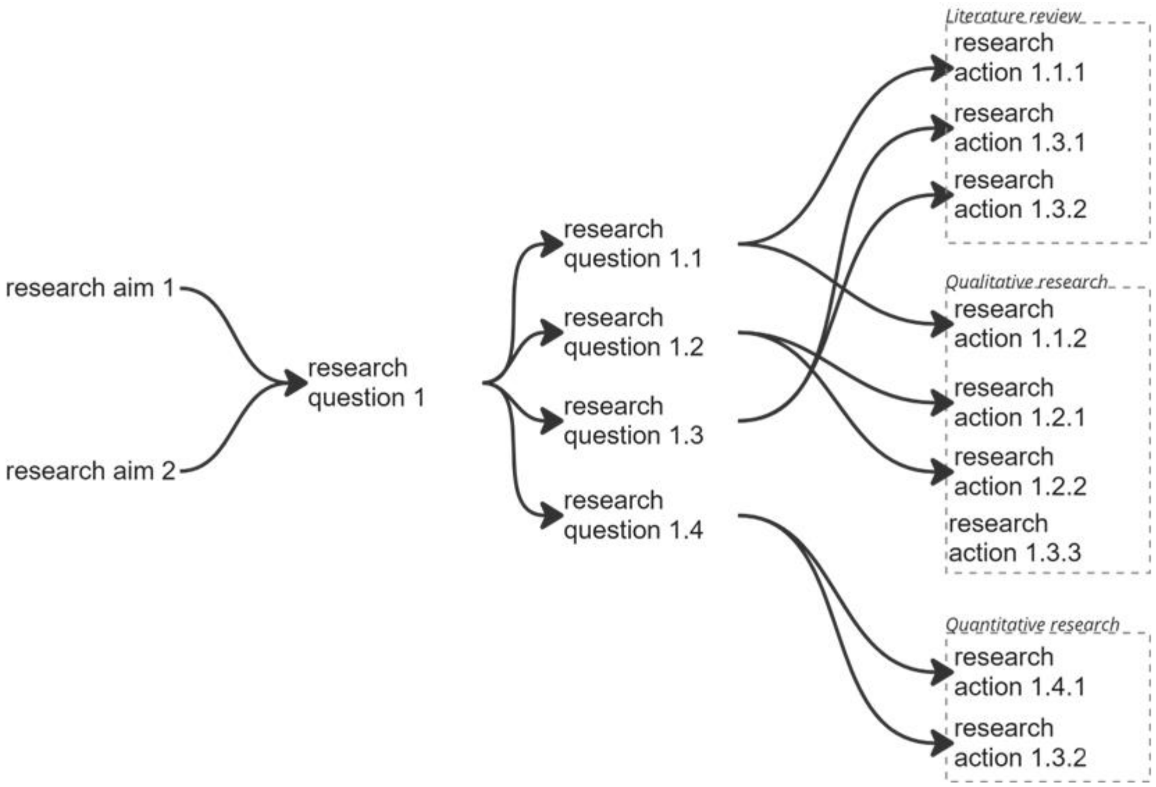


Figure 1: Link Between Research Aims, Questions and Actions

2 Literature Review

An organization is a system of interacting elements (i.e. employees, processes, and infrastructures) that is organized to achieve one or more stated purposes of the system (ISO/IEC 15288, 2005). Herbert Simon, in his seminal paper, views organization as a system in equilibrium. An organization receives contributions in the form of money or effort, as input parameters, and outputs inducements in return. A control group of the organization makes decisions and choices among alternatives to maintain the organization's equilibrium (Simon, 1947). The decision-making process in organizations has gained the attention of management scholars in academia since the late 1930s and 1940s (Hodgkinson & Starbuck, 2008). However, decision theory has long been the subject of interest among economists dating back to the 18th century. Although decision theory as an academic field has expanded into a multitude of disciplines over the years, it still revolves around two core concepts: normative and descriptive models. (March, 1978).

The normative decision-making model prescribes how people or organizations should behave to achieve optimal decisions (Rechtin & Maier, 2000; Simon, 1972). Rational behavior is the center of the normative decision model – also known as rational analysis – as normative theory is largely revolved around mathematical models such as game theory and statistical decision theory (Fox, 2015; March, 1978; Over, 2008). Most decision scholars agree that normative theory is the standard on which all decision-making processes should be based; any systematic deviations from the rational model are considered to be anomalies to the norms of decision-making (Fox, 2015; Kahneman, 1991; Rechtin & Maier, 2000).

The descriptive model, on the other hand, explains how people actually behave when making decisions (French, Bell, Raiffa, & Tversky, 2006; Over, 2008). This behavioral decision-making theory explores the systematic deviations from the normative model due to the emergence of heuristics and biases in the decision-making process (Baron, 2008; Kahneman, 1991; Over, 2008).

Current trends indicate that the technical decision-making process should be rational and adhere to mathematical objectivity, with many studies advocating for decision analytical tools of varying complexity, from straightforward procedures to complex mathematical models and simulations. Tang et al. (2022) recommended systems dynamic modeling and grounded theory to assess risks in technical decision-making for large-scale construction projects. For complex technical system design, Nemtinov et al. (2019) introduced a generalized model for decision support using sequential analysis and discrete optimization based on sophisticated mathematical models. Utilizing virtual modeling technology, Nemtinov et al (2021) developed information and logical models to enhance the decision-making process for equipment layout in virtual environments. Ginting et al. (2017) employed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodology as a decision support system to identify not only the optimal solution but also the solution that maximizes the distance from the least desirable outcome. Kranabitl, Faustmann, and Hick (2021) proposed a unique approach to technical decision-making by incorporating systems thinking, model-based systems engineering, and human factors to achieve sustainable and less biased decisions. Nevertheless, mathematical approaches to technical decision-making can be traced back to the latter half of the 20th century. Decision analysis tools, such as influence diagrams or decision networks (Howard & Matheson, 2005), multi-attribute utility analysis (Keeney & Raiffa, 1993), Simple Multi-attribute Rating Technique or SMART (Edwards, 1971), decision tree analysis (Raiffa & Schlaifer, 1961), and Thomas Saaty's analytic hierarchy process (Saaty, 1980), have been widely applied in both academia and industry due to their numerous advantages.

However, the study of behavioral aspects of decision-making process within a product development context is sparse. Only a few research studies have explored the existence of heuristics and biases in the technical decision-making process during product development, leaving a gap that needs addressing. For example, Siefert and Smith (2011) investigated industry data and identified several biases that influence technical risk management in engineering organizations. Other studies have confirmed the presence of biases such as confirmation bias and overconfidence bias in engineering design practices (Hallihan, Cheong & Shu, 2012; Zheng, Ritter & Miller, 2018; Nelius et al., 2020; Agyemang, Andreae & Mccomb, 2023). Moreover, McDermott, Folds, and Hallos (2020) identified cognitive biases specifically impacting systems engineering teams; biases like vividness bias, clustering illusion bias, and sample size bias can lead to suboptimal outcomes in systems engineering tasks. *Biased information passing* was also observed as a negotiation tactic in order to manage risk throughout the design process (Austin-Breneman, Yu, & Yang, 2016).

The literature review (Figure 2) aims to understand the evolution of decision theory research over the years and narrows its focus to a specific decision context: technical decision-making in product development in safety-critical, highly complex systems industries. Examining the latest literature on decision-making yielded a general explanation of the origin of decision theory. Based on the examination, many original papers on established decision theories, dating back to the 18th century, were studied to form the earlier decision theory discussed in Section 2.1. Jeremy Bentham's (1781) and Daniel Bernoulli's (1738) perspectives on the maximization of expected utility laid the groundwork for early decision theory research, marking the starting point of this literature review. The review continued to focus on rational decision-making theories, which were dominant in the first half of the 20th century (Section 2.2). However, Section 2.3 demonstrated counterarguments for rationality in decision-making, which has been gaining momentum in the latter half of the century. In parallel, the literature review on organizational decision-making theories, described in Section 2.4, sets the focus of this thesis. Finally, Section 2.5 reviewed academic and industry literature to explain the role of technical decision-making in product development processes.

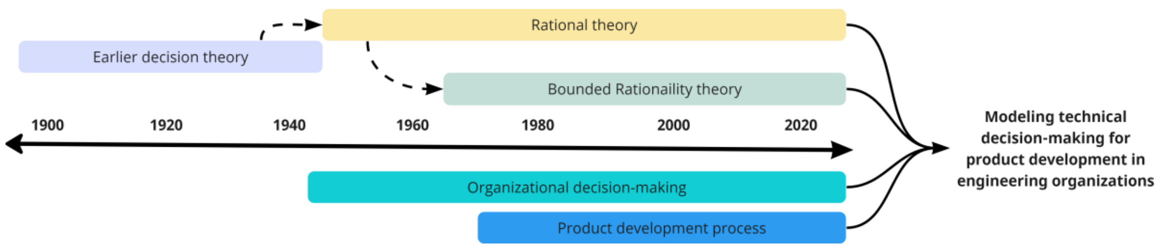
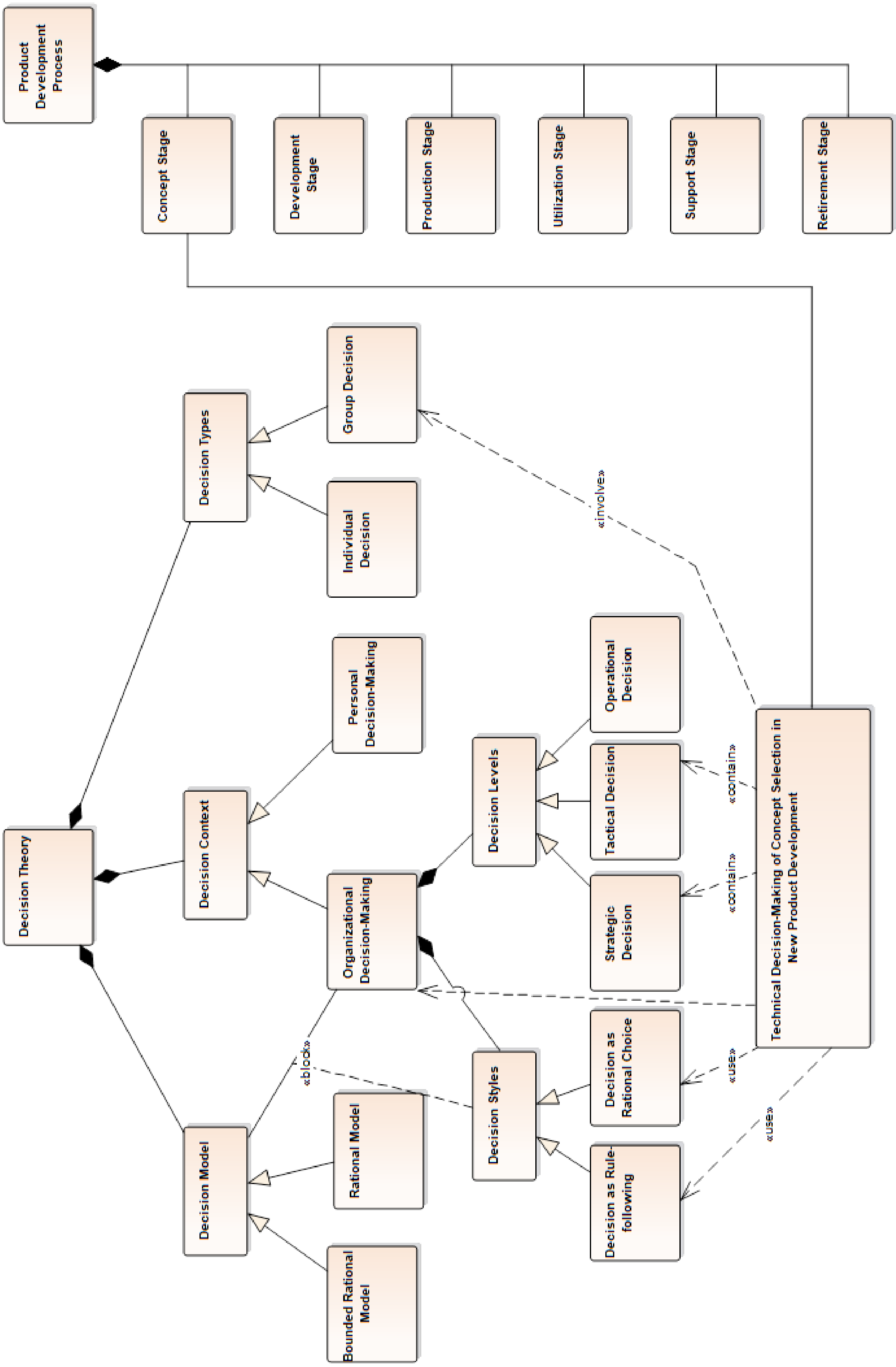


Figure 2: Literature Review Approach

A large part of the literature on decision-making focuses on the development and understanding of decision models: normative (or rational) and descriptive (or boundedly-rational). Decision theory can also be grouped into decision types, such as individual and group decisions, and decision contexts, for instance, personal and organizational (Figure 3). In organizations, decision levels – that is strategic, tactical, and operational – exist depending on the organizational hierarchical level.

Figure 3: Theoretical Framework of Decision-making Research[1]



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[1] Product development process model is adapted from ISO 24748-1

2.1 Economic Man

Early interest in the theory of decision-making can be traced back to Jeremy Bentham, a philosopher-economist, in 1789 (Edwards, 1954; Stigler, 1950). Bentham postulates that the goal of human action is to pursue pleasure and avoid pain, or in other words, to maximize utility (Bentham, 1781). Utility can be defined as a measure of preferences or satisfaction over goods and services which may include monetary value. Many early scholarships in decision-making were the result of the economic study of consumer behavior, in which utility theory played a central role.

Daniel Bernoulli in his notable paper, *Specimen Theoriae Novae de Mensura Sortis* (1738), describes that the value of an item is not solely based on its price, but rather the utility it yields to the consumers. The price of an item is dependent on the object and is the same for everyone, but it is the utility that varies between persons. He further suggested that one thousand ducats are far more valuable to a poor than a rich man, even though its monetary value is the same. Therefore, persons are assumed to maximize their expected utilities, while anticipating risks during their pursuit (Bernoulli, 1954). This theory is later called expected utility theory and has been in the interest of economists since the turn of the 20th century.

An economic man, or ‘homo economicus’, has always been a significant ‘figure’ in the economic field, as he is an ideal but fictional person representing objective rationality (Tittenbrun, 2013). In classical economic utility theory, economic man portrays humans as rational and self-interested agents who pursue their subjectively-defined ends optimally to maximize expected utility (Edwards, 1954). The “economic man”, however, has been a subject of debate across academic fields – from economics and mathematics to psychology – especially in the topic of decision-making (Fox, 2015).

Concerning decision-making, an economic man is postulated to have three properties (Edwards, 1954; March, 2002; Simon, 1955):

1. He has complete information about his environment. An economic man is assumed to have all of the knowledge required to make a decision and all of the outcomes arising from the decision in terms of probability distribution.

2. He has infinite sensitivity. Economic man also has access to continuous alternatives due to his infinite computational skills.
3. He is rational. Economic man can order his preferences of the alternatives into a stable system and make his decision to maximize utility. He is expected to have consistent values to compare alternatives in terms of their subjective values.

The maximization of utilities can be objectively studied if the utility is quantifiable. In the cardinal utility approach, utility is measurable, and humans can express their satisfaction with goods or services quantitatively – using cardinal numbers. The cardinal utility function uses a utility index with an interval scale to preserve preference ordering and, ultimately, to quantify subjectively ordered preferences. Therefore, classical utility theorists postulated that cardinal utilities are interpersonally comparable, and thus, the best economic policy can be derived from the maximum total utility of the sum of all members of the economy. (Edwards, 1954).

John Von Neumann and Oskar Morgenstern use the “Robinson Crusoe” model, an economy of a single person, as an example to explain and expand the expected utility theory of Bernoulli. Crusoe has certain desires and commodities and is expected to utilize them to obtain maximum satisfaction. In the “Crusoe” economy, he controls all variables and enables himself to maximize his utilities independently; therefore, he does not face the same maximization problem that occurs in the real world. In the social exchange economy of the real world, participants cannot maximize their utilities because they must depend on other participants. Certain commodities, which may be controlled by other participants, are needed to maximize certain desires. Thus, two or more people are expected to exchange goods or services. As each participant tries to maximize their utilities, it becomes a mixture of several utility maximization conflicts. (Von Neumann & Morgenstern, 1944).

Numerical measurement of utilities can only be applied in utility theory if an individual has completeness of preference, or in other words, can think rationally. Based on this premise, von Neumann and Morgenstern defined a set of axioms for expected utility theory that became the basis of von Neumann-Morgenstern utility theory:

1. An individual has a complete system of individual preferences. They must have well-defined preferences and can clearly decide between two or more alternatives.
2. An individual has transitive preferences. An individual can consistently decide their preferences in any decision-making scenario.
3. An individual's system of preferences is continuous. An individual's preference between two alternatives of any possible combination shall be continuous in the system of individual preferences. For example, if A is preferred over B, and B is preferred over C; therefore, the system will always result in a preference for A over C (Von Neumann & Morgenstern, 1944).
4. An individual preference has to be independent from irrelevant alternatives. An individual shall not yield to external alternatives but maintain the same order of preferences (Malinvaud, 1952; Samuelson, 1952).

As von Neumann and Morgenstern's discussion of expected utility theory became central in economic theories in the first half of the 20th century, other scholars had already expanded Bernoulli's discovery in different directions earlier in the 1800s. In the context of cardinal utility, marginal utility is defined by Friedrich von Wieser as "the smallest utility obtainable in the circumstances, assuming the most thorough possible utilization of the goods" (von Wieser, Malloch, & Smart, 1893). In other words, the utility of goods or services changes as their consumption increases. Heinrich Gossen stated that increasing the consumption of a product while keeping the consumption of other products constant, causes the marginal utility of the product to diminish, as it is now known as Gossen's First Law of diminishing marginal utility. The second and third laws further stipulate that individuals will optimize their expenditures so that the ratio of marginal utility to price is in equilibrium in order to attain maximum satisfaction with limited resources and that scarcity of a product is a precondition to economic value (Gossen, 1854). This particular subset of utility theory later developed into the economic law of supply and demand and helps economists study the behavior of consumers' decision-making processes (Dittmer, 2005).

If one school of utility theory posits that utility can be measured quantitatively in cardinal numbers, another school of thought argues otherwise; consumers cannot express their satisfaction objectively. The subjectivity of consumer satisfaction can be represented by preferences on an ordinal scale. So, instead of assigning numerical values to preferences, they are ranked qualitatively, according to ordinal utility theory (Edgeworth, 1881; Hicks & Allen, 1934).

Ward Edwards disputed the objective probability of expected utility theory as it does not fit any consumer behavioral models of the real world (Edwards, 1961). In risky decisions, gambling, for example, people would rather go for a lower monetary outcome with a higher probability of winning rather than vice versa (Edwards, 1954). Therefore, he suggested that individual preference of alternatives is subjectively evaluated. Leonard Savage's proposal of subjective probability measurement has two axioms:

1. All acts – outcomes of any scenarios – can be ranked
2. The ranked acts are rooted in sure-thing principle (Savage, 1954)

These axioms became the basis of subjective expected utility theory, in which the theory states that the utility of any outcome is subjectively evaluated by the person who makes the estimation (Edwards, 1961). Therefore, the probability of an alternative being chosen may differ from one decision-maker to another as the alternative's attractiveness is subjective to each individual.

Economic man can tell us a lot about the early beginning of decision-making study. The early foundation of decision-making theories is firmly grounded in the field of economy, where scholars attempted to formulate the behaviors of consumers as agents in an economic model through mathematical reasoning. Thus, mathematical formulas governing the maximization of consumer satisfaction in goods or services – also known as utilities – were furiously produced and debated by economists. However, all of these theories were rooted in one pre-condition; the economic agent must be rational.

2.2 Rational Model

In the history of decision-making, early theories predominantly focused on statistical probabilities and rationality. From Blaise Pascal and Pierre de Fermat's analysis of the probabilities in a simple dice game in the 1650s (A. W. F. Edwards, 1983) to Daniel Bernoulli's development of utility theory in the 18th century (Bernoulli, 1954), and Von Neumann and Morgenstern's game theory in 1944, these theories commonly viewed decision-makers as consistent and rational. The rational model of decision-making is described as a decision-maker possessing a "well-organized and stable system of preferences and a skill in computation that enables him to calculate, for the alternative courses of action available to him, which of these will permit him to reach the highest attainable point on his preference scale" (Simon, 1955). Consequently, there are many schools of thought on rational decision-making, among which game theory and decision analysis are prominent and will be discussed further below.

2.2.1 Game Theory

Von Neumann and Morgenstern applied their axiomatic treatment of expected utility theory – as explained in Section 2.1 – on a set of examples to study a strategic interaction between rational decision-makers, which they called a zero-sum game or game theory (Von Neumann & Morgenstern, 1944). The example became the precursor to many modern game theories that include the notable works of John Nash's equilibrium theory (Nash, 1951), Reinhard Selten's subgame perfect equilibria (Selten, 1965), and Leonid Hurwicz's mechanism design theory (Hurwicz, 1973).

The zero-sum game is a non-cooperative game that is played by at least two people and the end goal is purely monetary. In this game, neither goods nor wealth are created or destroyed. The sum of all payments received by all players is zero; hence, the zero-sum game. Therefore, if one player wins, the other loses. The foundation of a zero-sum game is the minimization and maximization of expected utilities, and in this context, monetary gains. According to Von Neumann and Morgenstern, in a two-player zero-sum game, the two players can either try to minimize maximum losses (i.e.: minimax theorem) or maximize minimum gains (i.e.: maximin theorem). If both players use equally dominant strategies, there will be an equilibrium point where both players will receive the same outcomes of the game, and this is called a saddle point. In order to optimize their overall payoff, it is wise for a player to mix strategies with the help of statistical probabilities, to conceal their strategies from the opponent. Therefore, game theory defines mathematical analysis to optimize strategies to maximize the utility of a player (Von Neumann & Morgenstern, 1944).

John Nash founded his equilibrium theory on the saddle point of the minimax theorem (Kaneko, 2005; Nash, 1950). He postulated that the set of equilibrium points in a two-person zero-sum game is simply a set of good strategies from both players. He also pointed out that saddle point does not only exist in a two-person zero-sum game, as it can also exist in a non-zero-sum game. His theory simply states that there is an equilibrium point in a non-cooperative game where if all players know each other's strategy and their strategies remain unchanged, there is no incentive for them to deviate from their initial strategy. However, a player can only maximize the pay-off using mixed strategies if and only if other players are using pure strategies; in other words, do not change their strategies (Nash, 1950, 1951).

Selten further refined Nash equilibrium in his subgame perfect equilibria theory. Nash equilibrium ignores the sequential nature of games and considers strategies as choices made only once at the start of the game (Osborne, 2004). On the contrary, the foundation of Selten's theory is based on the concept of sequential rationality: agents calculate and predict their opponents' strategy, on a move-by-move basis, based on the sequential structure of the game (Fudenberg & Levine, 1983). Therefore, Selten theorized that there exist sub-games within a game where the perfect equilibrium of each subgame occurs (Selten, 1965).

If conventional game theories propose strategies to forecast outcomes, mechanism design strategy takes the reversed approach: particular outcomes are first identified, mechanism is then devised to attain the specified goals. Mechanism design theory adopts an engineering approach to design economic systems. However, a mechanism in this context refers to an institution, procedure, or game that shapes the desired outcome (Maskin, 2008). As resource allocation is the center of economic theory, in which all of the economic agents involved are trying to maximize their own expected utility based on finite resources, Hurwiczs proposed that a mechanism must be designed to guide the economic agents in decisions to determine the flow of resources. As each agent contains private information for optimization problem, the problem can only be solved if this information is revealed truthfully to the principal. Therefore, the principal shall design a mechanism to be incentive-compatible for each agent, in which the information can be revealed truthfully and an equilibrium in the game of economic system can be achieved (Hurwicz, 1973).

Application of game theories in decision-making can also be found outside of the economic field, such as management, politics, and biology. Anthony Kelly utilized game theories in management science and introduced the concepts to organizational decision-makers in order to help them make better decisions in complex scenarios (Kelly, 2003). In politics, Andrew M. Colman likened a democratic government to a multi-person game of social choice. So, game theories and their strategies can be adopted in voting games, where the voters are the players and the outcome is their political representatives of choice (Colman, 1995). More interestingly, in 1973 Maynard Smith and Price applied game theory in biology to simulate conflicts between animals, whereas the animals were found to use *limited war* strategy in combat to avoid inflicting serious injury to their opponents. The strategy resulted in an equilibrium point where the outcomes were best for both sides and their species (Smith & Price, 1973).

Game theories have mainly helped economists to model and understand the economic systems of a multitude of agents with different needs, constraints of resource allocations, and complex flows of information and goods. However, game theories are not particularly useful in scenarios where decision-making is not a game of strategies, or when vague information and subjective needs are aplenty. The player has no opponent and makes decisions only to maximize his or her own expected utilities. Thus, such scenarios require a different approach to decision-making, such as decision analysis.

2.2.2 Decision Analysis

While Von Neumann and Morgenstern (1944), Nash (1950), Selten (1965), and Hurwicz (1973) explored the objective probabilities of games of strategy, other scholars, like Edwards (1961), used statistical analysis to examine the subjective probability of decision-making. Similarly, Howard Raiffa rejected the notion of mathematical objectivity in decision-making and proposed a methodology for incorporating vague and imprecise information into analysis through an iterative process; this method is known as decision analysis (Raiffa, 1968). He merged his earlier invention of the game tree, an early variant of the decision tree that extensively examines game theory, with subjective probability theory, laying the foundation for decision analysis for years (Buchanan & O'Connell, 2006; Fienberg, 2008).

Decision analysis, also known as statistical decision theory, is based on a set of axioms that guide decision-makers in systematically and logically approaching problems to derive alternatives with the highest expected utility using subjective probability (Keeney, 1982). This analysis extensively employs Bayesian statistical analysis and expected utility to determine subjective probability, partly due to its utilization of non-experimental sources of information (J. O. Berger, 2013; Fox, 2015).

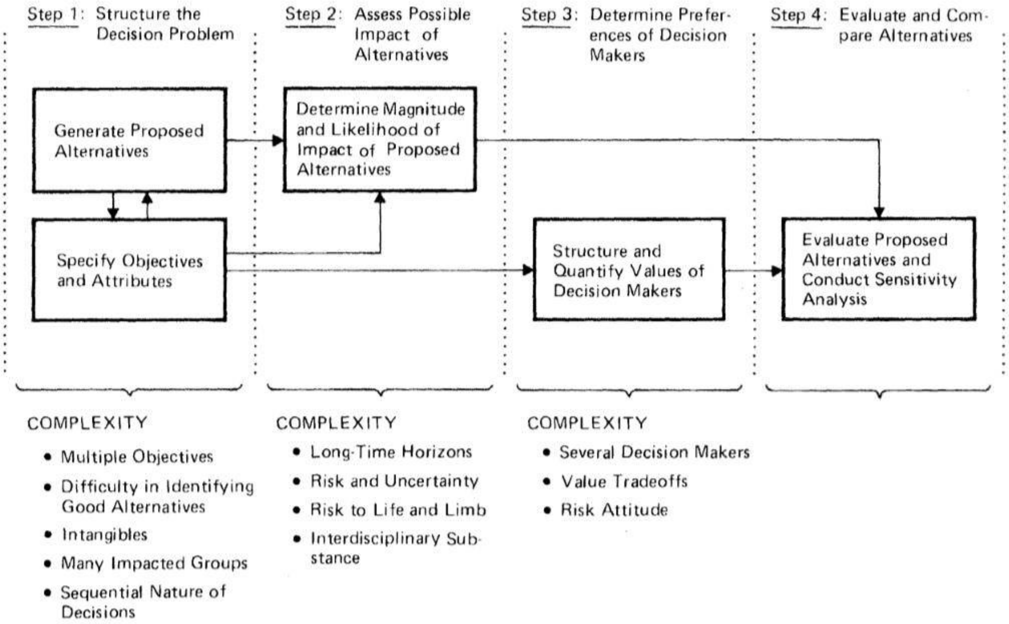

Figure 4: Interdependencies of Decision Analysis Steps (Keeney, 1982)

Ralph Keeney summarized the fundamentals of decision analysis in four steps (Figure 4):

1. Structure decision problems by defining objectives and generating alternatives. Alternatives can be defined by first creating objectives based on the consequences of alternatives. Then, rank the objectives in order of ambiguity and finally, identify attributes to measure the objectives.
2. Assess the possible impacts of the generated alternatives. These impacts can be assessed using a formal model that accounts for several components. Subsequently, specify the model inputs with deterministic or probabilistic information.
3. Determine the preferences and values of decision-makers. These preferences can be ascertained by first introducing terminology and ideas to ensure clear communication between analysts and decision-makers. Then, determine the general preference structure using single-attribute utility functions with a scaling constant. Thirdly, assess the utility functions to determine an appropriate risk attitude and scaling constants to ensure desirability attributes are appropriately defined. Finally, check for the consistency of the analysis using different processes and decision-makers.
4. Evaluate the generated alternatives against the preferences of decision-makers. (Keeney, 1982).

Although there are many variants of decision analysis – such as influence diagrams or decision network (Howard & Matheson, 2005), multi-attribute utility analysis (Keeney & Raiffa, 1993), and Simple Multi-attribute Rating Technique or SMART (Edwards, 1971) — this literature review focuses on Howard Raiffa’s decision tree analysis (Raiffa & Schlaifer, 1961) and Thomas Saaty’s analytic hierarchy process (Saaty, 1980) due to the popularity of their methods in the literature.

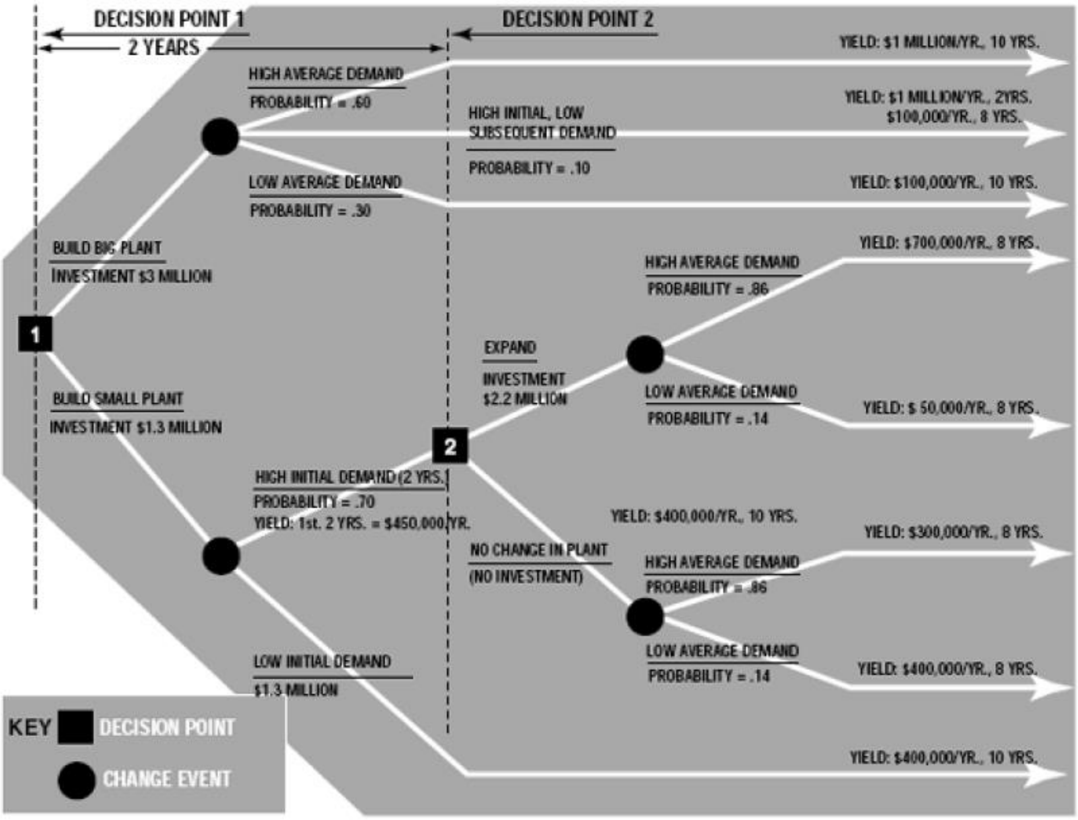

Figure 5: Decision Tree in Financial Analysis (Magee, 1964)

A decision tree (Figure 5) is a graphical and analytical representation of the decision-making process with multi-way branching that denotes decisions and chances (Raiffa & Schlaifer, 1961). The decision tree has been revised and updated over the years; however, the fundamental building blocks remain consistent and contain three types of nodes:

1. Decision node: Indicates a decision must be made.
2. Chance node: Indicates probabilities of outcomes.
3. End node: Indicates final outcome.

The tree begins with a decision node, where decision-makers choose from multiple alternatives. Each decision involves probabilities of success, represented by a chance node. If further decisions are needed, another decision node follows the chance node, and the tree grows through multiple stages of alternating decisions and chances. The decision process concludes with an end node, assigned an expected utility or pay-off off (Raiffa & Schlaifer, 1961). As illustrated in Figure 5, the decision tree enables the visualization of a relatively complex decision, with its various chances and pay-offs, in an easily understandable graphical format.

Not only does it assist decision-makers graphically, but the expected utility of each decision can also be statistically analyzed. The expected utility at a decision point is calculated by summing the product of each event's probability and its pay-off (Raiffa & Schlaifer, 1961). Any investment related to a decision must be deducted from this calculation, if applicable. For example, in the case of Figure 5:

- Build big plant: (\$(1 mil x 10) × .60) + (\$(1 mil x 2 + 0.1 mil x 8) × .10) + (\$(0.1 mil x 10) × .30) – \$3 mil = \$3.6 mil (Magee, 1964)

Decision tree analysis is widely taught in business schools and utilized in various industries, particularly for business decision-making (Fox, 2015). However, the effectiveness of this analysis in decision-making scenarios varies, as organizations often encounter challenges such as highly complex decision trees, a lack of expert inputs, and disconnection from top management (Ulvila & Brown, 1982). Users of decision trees may attempt to incorporate every conceivable scenario, but it is crucial to focus only on the most important elements and add subsidiary trees for more detailed analysis if needed. Additionally, decision tree analysis requires collaborative effort; thus, expert inputs are essential to ensure the analysis is comprehensive and robust, preventing decision-makers from being caught off guard by unexpected outcomes. Furthermore, without full backing from top management, both the execution of decision tree analysis and the implementation of resulting decisions can be challenging. It is also vital to address key management concerns to ensure alignment with the company's needs.

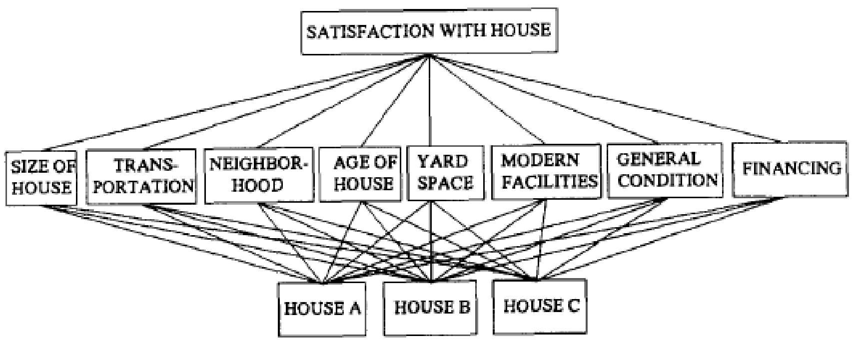

Figure 6: Analytic Hierarchy Process

The next decision analysis theory is the Analytic Hierarchy Process (AHP), proposed by Thomas L. Saaty (Saaty, 1980). This multicriteria decision-making process is widely used in various scenarios such as forecasting, development planning, and resource allocation (Saaty, 1980; Vaidya & Kumar, 2006). The process assists decision-makers by decomposing and structuring problems, goals, and stakeholders hierarchically to provide an overall view of their complex interrelationships (Figure 6). Although decision trees may share similar visual language, the hierarchy in AHP represents cut sets of a problem, while a decision tree illustrates multiple decision junctions. A set of alternative solutions is defined to anchor the selection criteria of a particular decision-making goal. The criteria are compared in pairs as scaled ratios, using a pairwise comparison matrix derived from the Eigen vector principle, allowing users to focus judgment separately on each selection property (Saaty, 1990). The comparison can be based on either data or the judgment of decision-makers.

Decision analysis moves away from the mathematical objectivity seen in traditional rational theories, introducing subjective evaluations of preferences and alternatives to incorporate vague information and individual needs. This approach is increasingly valued in organizations for providing objectivity and quantified analysis to supplement decision-maker's judgment. Although decision analysis is more practical in organizations compared to rational theories, organizations still need to be aware of its utility. Decision analysis should aid decision-makers in making informed decisions, but it should not be the sole basis for decision-making (Wright & Goodwin, 2009). This is due to the pitfalls of decision analysis, such as weak theoretical foundations, inadequate consideration of subjective and value components of decision problems, and poor analysis by users (Keeney, 1982).

The effectiveness of rationality in any decision-making tool is, however, contingent on the subjectivity of its users: humans. Studies have been conducted to assess and identify the effects of biases on particular decision analyses (Fischer, 1979; Hogarth, 1975; Slovic & Lichtenstein, 1971), revealing that human biases impact both formal and informal decision-making procedures (Tversky & Kahneman, 1974). This is because humans are boundedly rational.

2.3 Boundedly-Rational Model

The theory of rational decision-making and its four axioms of expected utility were heavily criticized by many scholars. One of the axioms stipulates that preferences are transitive; an individual can consistently decide their preferences in any decision-making scenario. An experiment conducted concluded that if subjects were allowed to judge indifferences among the alternatives, they tended to order their preferences differently most of the time (May, 1954). Other experiments have also shown the expected utility axiom of preference ordering can be violated due to variations in the probability of the alternatives and the risk aversion of decision-makers (Kahneman & Tversky, 1979). Human preferences are ever-changing, ambiguous, and inconsistent. Even though people are aware of the inconsistency, they often do little to resolve it (March, 2002). Rational theories further assume that decision-making is static; however, it evolves over time. People first specify preferences and then choose actions, discovering new preferences through experiencing the consequences of those actions (March, 1976).

Rationality in decision-making can be bounded in a variety of ways. Herbert A. Simon introduced the concept of bounded rationality, which has since become a central point in behavioral economics (Kahneman, 1991). Human rationality is bounded due to the nature of human limitations in formulating and computing complex problems, and in processing information (Simon, 1957). Moreover, Simon added that unknown variables in the system of preferences may add to the risk and uncertainty in decision-making. Rational decisions can also be constrained due to incomplete information about alternatives or consequences. In some rational models, it is assumed that a decision-maker knows the probability distribution of utility in a set of possible alternatives. Even if the system of preferences is known and information about alternatives is complete, the complexity of arriving at the most rational course of action is almost impossible for any human to reach (Simon, 1947, 1972). Therefore, in reality, human rationality is extremely crude and limited compared to the rationality required by game theory models (Simon, 1955).

Limited rationality can be attributed to the conservative information processing of the human brain due to limitations in memory organization and information retrieval

(March, 1978). Numerous experiments comparing humans and statistical probability models have shown that human subjects consistently fail to extract as much information as the data may contain. Humans are rather competent at analyzing the diagnostic impact of data but fail to aggregate the data properly (Edwards, Phillips, Hays, & Goodman, 1968). Due to this limitation of human cognition, humans tend to adapt by “satisficing”, a portmanteau of satisfy and suffice, where humans pursue a course of action that meets, rather than maximizes, their minimum utility requirements (Simon, 1956).

Nonetheless, incomplete knowledge about the world does not necessarily hinder individuals from making effective decisions. Simon (1956) introduced the concept of partially ordering payoffs, suggesting that satisfactory outcomes can be attained by reaching a specific threshold of agreement among available alternatives, known as an aspiration level. However, this aspiration level is dynamic, contingent on the ease of finding satisfactory alternatives and an organism's level of persistence. More persistent organisms tend to exhibit greater rationality, enabling them to identify and partially rank the payoffs of various options. However, this level of rationality is not a universal trait among organisms. Simon further asserted that there is no compelling evidence supporting the notion that humans can consistently make choices in situations of any complexity, as prescribed by the classical rational choice model (Simon, 1955). Consequently, the study of decision theory should not rely solely on the normative theory of the rational model but should also acknowledge the inherent inconsistency in human cognition.

Over the course of the 20th century, the theory of choices has evolved from deterministic to stochastic models (Edwards, 1954). In the deterministic or rational model, choice preferences are absolute, and the order of preference remains constant and consistent. However, stochastic models introduce the notion that preference sets are probabilistic in nature. The assessment of the importance of preferences is subjective, making the probability of utilities inherently subjective as well (Edwards, 1954). It is widely recognized that Ward Edwards defined the domain of behavioral decision theory by amalgamating concepts from classic economic theory and decision theory into the field of psychology (Kahneman, 1991). Behavioral decision theorists postulate that human behaviors may deviate from optimal decision-making; for example, heuristics can reduce the information-processing requirement of rational decision-making (Hodgkinson & Starbuck, 2008). The availability heuristic causes people to make decisions based on immediate past events because of their perceived importance, while the representativeness heuristic skews people's probability of preference according to the person's generalizations of similar events. Furthermore, Kahneman and Tversky postulated that people tend not to follow the statistical theory of prediction in making judgments under uncertainty. Instead, they rely on a number of heuristics to reduce the complexity of assessing probabilities and predicting outcomes. This may lead to poor outcomes or severe and systematic failures (Kahneman & Tversky, 1973; Tversky & Kahneman, 1974).

By comparing the present Merriam-Webster Dictionary's definition to the definition provided in the 1828 version, it can be observed that the definition of bias has evolved towards a more negative connotation over the years. In the 1828 version, "A leaning of the mind; inclination; prepossession; propensity towards an object, not leaving the mind indifferent" had a more neutral tone (Merriam-Webster, 1828). Whereas, the definition in the present version, "an inclination of temperament or outlook especially: a personal and sometimes unreasoned judgment", paints bias in a negative light (Merriam-Webster, 2023). This shift in perspective is also clearly seen in academia. In comparison, academic literature defines cognitive bias as an intrinsic systematic error of the human brain that produces distorted representations of objective reality (Haselton, Nettle, & Murray, 2015), while social bias is a systematic error in how we perceive others (Ross, Amabile, & Steinmetz, 1977).

Many earlier studies on judgment and decision-making painted an unfavorable picture of heuristics and biases. However, heuristics and biases are not necessarily detrimental to decision-making. Studies of heuristics-and-biases typically focus on errors of judgment. However, they should not be seen as errors but rather as an incapability to achieve certain standard yet abstract rules. The errors cannot simply be corrected by learning or training (Kahneman, 1991). Some scholars argue that gut feelings and snap judgments used by humans are not necessarily inferior to probability-based decision theory. Based on their observation of a few professionals who develop expertise, the scholars observed that the experts tend to rely on heuristics because the process is more organic and less systematic than in decision analysis models (Fox, 2015). It is not only laypeople who are prone to base their judgments on intuition. Experienced researchers with deep knowledge of statistical analysis have also been observed to make intuitive judgments when presented with data with insufficient analysis (Kahneman & Tversky, 1971, 1973).

Heuristics cannot be likened to a situation where people make decisions based on luck. It is a highly developed non-logical form of reasoning based on both unconscious impressions of the physical and social environment, and formal knowledge through learning (Barnard, 1938). Although most organizations value decision analysis as a valuable tool in making concrete judgments, too much rationality in decision-making results in an insurmountable amount of analysis and causes people to feel less committed to action (Hodgkinson & Starbuck, 2008). Conversely, while heuristics are considered irrational, Robbins et al. suggest supplementing decision analysis with heuristics (Robbins & Judge, 2001). Furthermore, in situations where uncertainties cannot be optimized and the data fed into the analysis is insufficient, using a rule of thumb would be a better option (Hutchinson & Gigerenzer, 2005). Finally, the study of human decision-making interests not only economists and psychologists but also researchers investigating the decision process from sociological and biological perspectives.

In light of all this, this thesis defines bias as an inclination or predisposition of the mind towards a particular viewpoint or outcome, which represents a deviation from the position that would be predicted by rational decision-making.

2.3.1 Psychological Factors in Decision-Making

One of the earliest and most well-developed theories on the effects of human psychology in decision-making is prospect theory. Prospect theory provides an alternative model to counter the claim of expected utility theory as a descriptive model of decision-making under risk (Kahneman & Tversky, 1979). Kahneman and Tversky criticize expected utility theory for being insufficient to describe the naturalistic behavior of human decision-making. Most field investigations validating expected utility theory provide crude tests of qualitative predictions, while experiments conducted in laboratories often involve repetitive studies of very similar decision scenarios, such as small-stakes gambling. Both methods of study lack the capability to reflect or simulate real-life decision processes.

Kahneman and Tversky hypothesize that people usually make decisions by evaluating and omitting alternatives to simplify choice, and "people normally perceive outcomes as gains and losses, rather than as final states of wealth or welfare" (Kahneman & Tversky, 1979). The reference point for these gains and losses is first coded relative to the current assets of the decision-maker. The outcomes, or prospects, can be simplified by combining them with identical probabilities or segregated if they contain riskless components. Following that, people tend to cancel out options that lead to the same outcomes through different routes, a phenomenon known as the isolation effect, to further simplify the alternatives.

People also tend to be risk-averse when there is a probability of gain but risk-seeking when facing potential losses (Kahneman & Tversky, 1979; Markowitz, 1952; Williams Jr, 1966). This is visualized in Figure 5, where the preference between negative outcomes is a mirror image of the preference between positive outcomes; this pattern is aptly called the reflection effect. Furthermore, the certainty effect can also be seen in the human decision-making process; where outcomes with a high level of certainty are ranked highly in the system of preference, even though the gain may be lower than an outcome with lower certainty (Tversky & Kahneman, 1974). The studies conducted by Kahneman, Tversky, and others have shown that human psychology plays a huge part in decision-making.

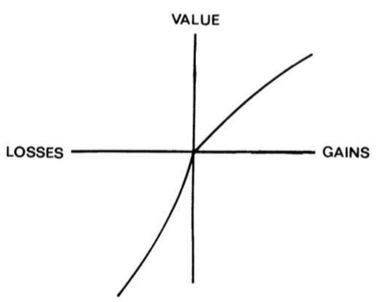

Figure 7: Hypothetical value function (Tversky & Kahneman, 1974)

The examination of decision-making from a psychological perspective is defined by its focus on using the normative theory of rational decision-making as a foundational framework for behavioral analysis. It prioritizes cognitive processes to elucidate why choices deviate from the rational model, often overlooking emotional and social influences (Kahneman, 1991). The normative theory of decision-making describes how people should make decisions rationally, while the descriptive theory explains how people actually make decisions. If we regard the rational model as the ideal strategy, it becomes a fitting reference model for evaluating and contrasting the bounded rational approach of a behavioral decision model. Additionally, when viewed from a psychological standpoint, Daniel Kahneman categorizes cognitive processes into two systems: System 1 and System 2. System 1 operates automatically and intuitively, overseeing abstract thinking and involuntary actions. In contrast, System 2 is responsible for conscious thinking and calculation, allocated for tasks or decisions that require more effort and attention (Kahneman, 2011). Moreover, risk preference and estimation are subject to human biases. The propensity to embrace risk differs not only among individuals but also depends on the severity of potential consequences. Furthermore, the assessment of risk can be linked to the limited information available about the problem and its participants and tends to be influenced by the decision-maker's personal experiences and current predicament (March, 2002).

One of the major developments in behavioral decision theory in psychology is the relationship between personality and decision-making. Several studies have examined personality variables in decision-making in various situations, particularly risky decisions. One of the earliest studies on personality variables is on the level of aspiration effect on decision-making, conducted by Lewin and his team (Lewin, Dembo, Festinger, & Sears, 1944). According to the study, a person's aspiration level influences their “goal behavior” or action in decision-making. The behavior can be further decomposed into goal striving (the effort a person allocates towards achieving a decision), and goal setting (the level of accomplishment a person wishes to attain for their decision). The aspiration level is determined by assessing goal discrepancy, which represents the variance between the level of one's most recent performance and the desired goal behaviors for the current event. Lewin et al. discovered that aspiration level can also be linked to three factors: success seeking, failure avoidance, and cognitive probability judgment. For example, in clinical studies of school children (Sears, 1941), the group with low discrepancy level exhibited higher success in academics and higher cognitive ability with more “realistic” goal settings. Atkinson (1957) views aspiration or motivation level by stating that there are two kinds of people: those for whom the motivation of seeking success is greater than avoiding failure and vice versa. In a different study, Block & Petersen (1955) claimed that decision-makers with high confidence levels make mature decisions. It is noted that overly confident people are more rigid in making decisions, while overly cautious people are more introspective. Decision response time can also offer insights into the personality of the decision-maker. For example, a fast decision in an easy situation tends to revert to an overcontrol mechanism when confronted with a challenging situation as a means of coping with stress. Conversely, people with high sensation-seeking personality traits have a need for arousal that can only be provided in complex, intense, and risky experiences (Lauriola & Levin, 2001). Separate studies reported that high sensation seekers tend to take more risk, by betting more and at higher odds in gambling tasks (A. Wong & Carducci, 1991; Zuckerman, 1979). In betting experiments conducted by Scodel, Ratoosh, and Minas (1959), it was also observed that individuals with a greater need for achievement and a strong understanding of probability in risk assessment tended to exhibit a conservative approach to decision-making, opting for less risky alternatives.

There are also studies related to Jungian psychological types and cognitive styles with strategic choice patterns in decision-making (Hough & Ogilvie, 2005; Nutt, 1993). One of the most popular of Jung's typologies is the Myers-Briggs Type Indicator, which is built on two personality attitudes: extroversion and introversion, with four functions or modes of orientation: thinking, sensation, intuition, and feeling, yielding 16 personality types (Myers, 1962). Myers et al (1985) expanded the theory by combining dichotomies into four decision-making styles: Sensor-Thinkers, Sensor-Feelers, Intuitive-Thinkers, and Intuitive-Feelers. The information-gathering dichotomy (sensation, intuition) explores how decision-makers search for information, either through the five senses or via intuition. The decision-processing dichotomy (thinking, feeling) explains how they evaluate alternatives and make decisions, either via logic and basic truth or through analysis of personal warmth.

Psychological analysis of decision-making can only describe how decisions are made based on the correlation of data gathered through field testing and in laboratory settings using statistical analysis. However, it does not explain the cause of the decision process. Hence, exploration of human reasoning at a biological level may provide insights into the cognitive process of decision-making.

2.3.2 Biological Contributions in Decision-Making

Psychologists have provided a higher-level understanding of the relationship between cognition and decision-making. However, research on decision-making in biology is primarily undertaken by neuroscientists, given that the core processes of human cognition and decision-making are localized within the brain. Rapid advancements in neuroscience allow for deeper analysis of cognitive processes at a molecular level.

The prefrontal cortex of the human brain is known to be responsible for cognitive functions. Thus, damage to the prefrontal cortex can impair somatic markers – feelings in the body associated with emotions – and may compromise decision-making (Bechara, Damasio, & Damasio, 2000; Naqvi, Shiv, & Bechara, 2006). The processing of rewards in the human brain can be attributed to the striatum, a dopaminergic neurons-rich area. It plays a critical role in assessing values and reward predictions, providing a link between rewards and decision theories (Sanfey, 2007). Neuroimaging work on reward processing has supported the claims of prospect theory. Studies have shown that neural signatures of reward are not fixed on the objective value of the outcomes but by their relative value, gains or losses, to the reference point (Breiter, Aharon, Kahneman, Dale, & Shizgal, 2001; Holroyd, Larsen, & Cohen, 2004). The speed and accuracy of optimal decision-making can also be explained in the context of neuroscience. The cortico-basal ganglia networks of the brain facilitate speed-accuracy adjustment by employing distinct yet unknown mechanisms (Herz et al., 2017).

The field of neuroscientific research in decision-making has made significant advancements, critical in moving the decision-making field forward. To explore the underlying mechanisms of decision-making, investigations into the inner workings of the decision-makers themselves will yield a better understanding of human decision processes, both qualitatively and quantitatively. Furthermore, there have been efforts and progress in replicating and simulating biological neural networks in learning and decision-making, namely artificial neural networks (Jordan & Mitchell, 2015; Kontschieder, Fiterau, Criminisi, & Rota Bulo, 2015). However, this thesis will not delve into this realm but rather focuses on understanding decision-making in organizations through a more holistic view of decision-making in a social context.

2.3.3 Sociological Influence on Decision-Making

Behavioral decision-making can be viewed through the lens of individual freedom of choice, where a person can freely make decisions and act on them. However, as humans form societies, they directly and indirectly influence each other during the decision-making process. Along with psychologists, sociologists have also rejected the traditional model of rational choice, including their own version of sociological rational choice theory (Hechter & Kanazawa, 1997), which assumes decision-makers are maximizing utilities. Furthermore, rational models do not account for the ever-changing values and preferences of individuals in the context of society. Individuals sometimes align with the behaviors and actions of their social group to arrive at collective decisions and actions (Heckathorn, 1996). They also tend to apply recognition heuristics and adapt their decisions based on perceived societal norms; a phenomenon known as ecological rationality (Goldstein & Gigerenzer, 2011). Thus, sociologists focus on the role of cultural and contextual factors in decision-making, such as the availability of alternatives and people's opinions.

The number of choices available to a cultural or social group can be linked to variations in social orientation (Yates & de Oliveira, 2016). In some cultures, self-expression and freedom of choice are highly valued, while in others, social approval in the decision-making process is expected. Individualistic cultures promote creativity and divergent thinking, thus producing unique options. These variations can increase or decrease the number of choices available to actors within a particular cultural group (Goncalo & Staw, 2006). In the information-searching phase of decision-making, the amount and combination of information techniques vary from one culture to another (Choi, Choi, & Norenzayan, 2004). Choi et al (2004) state that due to East Asians' holistic assumptions about the universe, they prefer to consider a multitude of information before making a decision, in contrast to Westerners' preferences. Furthermore, in cultures where holistic thinking is prevalent, cultural agents will avoid contradictory information. For example, when confronted with conflicting information, the Chinese are more likely than Westerners to avoid scrutinizing each piece carefully but to make a compromise between them.

The behaviors of others, as in societal norms, can also heavily influence decision-making. People are more likely to adopt certain behaviors or decisions when the majority, with whom they share the same social space, behave similarly. An experiment conducted to study the effect of providing guidelines on energy consumption in a neighborhood yielded a surprising result: households are susceptible to the pressure of social norms regardless of the norms' constructive or destructive nature (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). Social norms also have different impacts on decision processes based on cultural settings. In cultures with high expectations of social conformity, social groups are more likely to compromise in decision-making to conform with others (Briley, Morris, & Simonson, 2000).

The study of decision-making in sociology has not advanced considerably compared to other domains, mainly due to sociologists' reservations about the validity of rational choice theory in their field (Hechter & Kanazawa, 1997). However, it is interesting to note how social context plays a significant role in shaping individual decision processes. Management scholars have taken a step further to study these phenomena in organizational behavior, which is explored in Section 2.4.

2.3.4 Heuristics, Cognitive and Social Biases in Decision-making

Heuristics and biases, as discussed in previous sections, are integral to the behavioral model of decision-making. Heuristics is a mental shortcut, or rule-of-thumb, where people base decisions on their intuitions to make decisions quickly or to avoid the taxing information-processing requirements of the rational model (Hodgkinson & Starbuck, 2008; Robbins & Judge, 2001). There are two types of biases discussed in this thesis: cognitive and social biases. Cognitive bias is an intrinsic systematic error of the human brain that produces distorted representations of objective reality (Haselton, Nettle, & Murray, 2015), while social bias is a systematic error in how we perceive others (Ross, Amabile, & Steinmetz, 1977). Heuristics and biases are commonly used together in the literature, as “the heuristics of judgment and choice are identified by the biases they tend to produce” (Kahneman, 1991). The following are some of the most common biases extensively discussed in academic literature.

The representativeness heuristic is a condition in which a person picks an outcome based on the degree of resemblance of the outcome with stereotypes in the person’s mind (Hodgkinson & Starbuck, 2008; Tversky & Kahneman, 1974). This heuristic is not affected by the decision-maker’s judgments of probability because probability is often mistaken for similarity. For example, if a subject fits a stereotype of a librarian and people are asked to choose the probability of the subject’s occupation from a list (e.g., farmer, salesman, pilot, librarian), those with representativeness heuristics tend to predict the subject is a librarian, even though there are more farmers than librarians in the population, hence, the probability of the subject being a librarian rather than a farmer is higher (Tversky & Kahneman, 1974).

The availability heuristic is a mental shortcut where people make decisions based on the ease with which instances can be brought to mind (Tversky & Kahneman, 1974). Instances that are more vivid or recent, evoking emotions in memory, are more likely to be readily available. For example, managers often give higher ratings to recent employee behaviors and performance during appraisals (Robbins & Judge, 2001). Similarly, retail managers might predict a competitor’s failure if there is recent news of their business struggles (Hodgkinson & Starbuck, 2008).

With the anchoring bias, people tend to set an initial point of estimation and adjust their final decision or estimation based on new information (Tversky & Kahneman, 1974). Depending on the initial value setting and the final adjustment range, this bias can cause a significant departure from the actual target. For instance, in business negotiations characterized by high uncertainty, the initial offer carries significant weight as it establishes the starting point and direction for the discussions. An experiment examining the influence of the first offer on negotiation outcomes indicated that final agreements tend to be more favorable to the party that made the initial offer (Galinsky & Mussweiler, 2001).

The framing effect bias arises when the same information is presented (or framed) differently, without changing its objective facts, causing people to interpret it differently. Kahneman and Tversky (1981) discovered this phenomenon while studying the framing effect in decision-making, concluding that slight variations in framing can cause significant variations in preferences. In technical decisions, experienced and objectively-oriented decision-makers tend to succumb to framing bias, making inconsistent choices even when faced with the same problem in different frames (Duchon, Dunegan, & Barton, 1989). Clustering illusion bias is the tendency to see small clusters of data points in random distributions as non-random (Gilovich, 1991). This bias leads to the perception of meaningful patterns that do not actually exist, akin to a false positive error in statistical hypothesis testing (Blanco, 2017).

When people are fixated and committed to a decision, even though all information indicates otherwise, they are subject to escalation of commitment bias (Staw, 1981). Individuals are inclined to escalate their commitment to a decision when they are heavily invested in terms of time and money, or they perceive themselves as responsible for poor performance (Staw, 1976). They will de-escalate their commitment if future gains seem less likely, but double down if failures are imminent, hoping to recoup losses (Staw, 1981). However, contrary to conventional wisdom, rational thinking increases individuals' inclination toward escalation of commitment (K. F. E. Wong, Kwong, & Ng, 2008).

Default effect bias is a component of nudge theory, where the likelihood of choosing an option increases if it is made the default. People tend to base their decision on the suggested default option when they believe such an option is an implied endorsement due to its merits, or when it frees them from laborious calculation (Dinner, Johnson, Goldstein, & Liu, 2011). For example, a case study on organ donation shows that decision-makers have a very high tendency to choose the default choice, even with high stakes (Johnson & Goldstein, 2013). In most cases, the default setting is deliberately chosen to simplify decision-making, reduce risk, or, more deviously, increase profitability (Goldstein, Johnson, Herrmann, & Heitmann, 2008).

Optimism bias can be described as “the difference between a person's expectation and the outcome that follows. If expectations are better than reality, the bias is optimistic; if reality is better than expected, the bias is pessimistic” (Sharot, 2011). Optimism bias leads to inaccurate forecasts and inflated benefit-cost ratios in projects, usually due to managers’ tendencies to intentionally overestimate benefits and underestimate costs as strategies to gain approval for their projects (Flyvbjerg & Flyvbjerg, 2013).

In confirmation bias, people are biased towards information that reaffirms their preexisting hypothesis and past choices, and discount information that undermines their decisions (Plous, 1993). Even though decision-makers are supposed to gather information objectively, their selective perception leads them to actively look for and accept information that confirms their preconceived understanding of events (Robbins & Judge, 2001). Confirmation bias is a complex phenomenon with high dependency on the context and information of a decision space, where a decision space defines the range of alternatives available to the decision-maker (Klein, Pfaff, & Drury, 2008). However, some general observations can be made: first, people seem to prioritize positive things and relations more than negative ones, and second, confirmation bias seems to arise from the relationship between cognitive and motivational processes (Klayman, 1995).

Belief revision or conservatism bias refers to humans’ tendency to be conservative in revising their beliefs when presented with new evidence (Edwards, 1968). Edwards conducted experiments comparing human decision behavior with the outputs of Bayes’s statistical analysis and concluded that, while humans do revise their opinions based on new information, the extent of the revision remains insufficient as expected in rational analysis.

Choice-supportive bias involves the creation of inaccurate memories of past decisions, which tend to enhance the chosen option and diminish those left unchosen (Lind, Visentini, Mäntylä, & Del Missier, 2017). This bias results from humans’ tendency to reconstruct their memory upon gratifying emotions to minimize regret, thus believing such a choice was the better option (Mather & Johnson, 2000; Mather M, Shafir E, & Johnson MK, 2000).

In a social group, group members are expected to conform to the standards and consensus of the group, which can cause social conformity bias (Kiesler & Corbin, 1965). The need to conform to society or a social group can be motivated by the accuracy of the decision, affiliation with the group, and maintenance of a positive self-concept (Cialdini & Goldstein, 2004). Conformity bias can also result from the individual need to gain social approval; individuals often engage to build rewarding relationships with the social group and thus enhance their self-esteem. Additionally, culture influences the intensity of social conformity. In collective cultures, people are more likely to comply with a request compared to those from individualistic cultures (Cialdini, Wosinska, Barrett, Butner, & Gornik-Durose, 1999).

Groupthink bias causes members of the group to pressure other members to conform to their views and suppress lone dissenters (Janis, 1971). If conformity bias is an individual instinct to conform to the group, groupthink is a rationalized conformity of a social group imposed on its team members (Whyte Jr., 1952). Symptoms of groupthink include group members' rationalization of assumptions against any resistance even when the assumptions are proven wrong, pressure on those who doubt or express dissent about the group's assumptions, a sole dissenter's tendency to keep silent to avoid deviating from the group's views, an unquestionable belief in the inherent morality of the group without considering the ethical consequences of their decisions, and finally, the illusion of unanimity: if no objection is made, it is assumed the assumptions are in full accord. (Janis, 1971; Robbins & Judge, 2001).

2.4 Organizational Decision-making

Based on previous discussions, much of the literature on decision theory focused on individual decisions, as opposed to group decisions, examining choices and decisions made independently of social context. This thesis, however, explores decision-making in two different contexts: personal decision-making and organizational decision-making. It is crucial to differentiate between personal and organizational decisions and investigate the dynamic interaction between individual and group decisions in organizations. A deeper analysis of decision-making processes also reveals the different decision levels – strategic, tactical, and operational – and decision types, such as rational choice and rule-following at the organizational level.

Thus far, economic scholars have been investigating how personal decision processes affect the production and consumption of goods and services. Although it may seem that these scholars examine decision-making through the lens of socio-economic exchange, emphasizing mutual reliance among participants in such exchanges, economic decision theories have predominantly been about personal decisions aimed at maximizing individual utilities. As discussed in the previous section, sociologists have challenged this view, arguing that social context plays a significant role in personal decision processes and that humans make decisions taking into consideration others' inputs. To this end, management scholars also have studied the effects of human psychology and interactions within organized units on decision processes since the 1940s. Herbert Simon (1947), in his book "Administrative Behavior," viewed organizations as complex interactive systems. Examining human administrative behavior in organizations, he concluded that the decision-making process is the core axis of any organization and that this process is based on the logic and psychology of human decisions. He was a long-standing opponent of the rational model of decision-making and proposed the concept of "administrative man" as a more realistic version of the "economic man." The administrative man (Simon, 1947):

- Views problem space in a simplified manner,
- Seeks only a limited number of alternatives and the information about the consequences of alternatives,
- Do not try to maximize utility but merely to find satisfying alternatives,
- And finally, makes decisions mainly based on heuristics, which can be derived from his limited knowledge.

However, an organization may have more than one administrative person at a time; thus, the interactions among a group of these individuals trigger an interesting dynamic in organizational decision-making processes.

Organizational decision-making can be viewed as an ecology of complex, intra- and inter-connected decision processes. It is not a linear process where decisions are made sequentially. Instead, it is a systemic property of interactions among decision-makers within an organization and between different organizations (March, 2002). Due to the interactions among individuals in a system of decision-makers, emergent properties – such as friction and cooperation among decision-makers – may influence how the system makes decisions collectively. Therefore, it is important to understand some characteristics that differentiate organizational decision-making from personal decision-making, such as ambiguity of information and preferences, longitudinal context, importance of incentives, repeatability of decisions, conflicts among decision-makers, volatility of the organization, and decentralization of decision-making.

First of all, uncertainty of information and ambiguity of preferences are persistent in organizations. As organizations generally make complex decisions, the information required for these decisions is exponentially larger than that needed in personal decision-making. The uncertainty and ambiguity in organizational decision-making can be attributed to an inadequate understanding of the decision space, lack of information about alternatives and their consequences, and indistinguishable alternatives (Lipshitz & Strauss, 1997).

Shapira (2002) argues that organizational decision-making is a longitudinal process where the decision-makers are the active participants who influence and bear the impacts of the decisions. Moreover, due to the interconnected nature of organizational decision-making, other members of the organization may also be affected by the consequences, whether or not they contribute to the decision process. On this note, although personal decisions may also impact other actors in a particular social group, the effects may not be as pronounced and immediate as in an organizational setting.

Furthermore, incentives and penalties would have significant ramifications in organizational decision-making. Since organizational decision-making is embedded in a longitudinal context, the effects are amplified, and thus, the survival instincts of organizational actors may come into play (Shapira, 2002).

Repeatability of decision processes is also common in organizations. Executives may have to make the same decisions repeatedly, during which heuristics and biases may influence their judgment. For example, an intuitive manager may view repeated decisions as routines, thus reaching conclusions too quickly, ignoring relevant information, or relying on instinct, even when the decision may be inaccurate (Gasser & Agor, 1987).

Conflict between decision-makers also plays a more significant role in organizational decision-making as compared to individual decision-making. Shapira (2002) states that in an organizational setting, personal agendas and conflicts of power rather than rationality among decision-makers may determine decisions rather than rationality based on the decisions' parameters. More so, conflicts and disagreements may also improve organizational decision-making. Dialectical inquiry and devil’s advocacy have been shown to lead to higher-quality decisions compared to group consensus (Schweiger, Sandberg, & Ragan, 1986). Dialectical inquiry, based on the dialectic method, investigates conflicting and competing ideas to produce emergent theories (Berniker, Mcnabb, Berniker, & Mcnabb, 2006). Devil’s advocacy uses a similar approach, where the investigator purposely adopts an opposing view from the subject to explore the topic further.

Moreover, organizations are volatile in terms of their actors and preferences. Cohen, March, and Olsen (1972) equate organizations to organized anarchies, where participation in organizational decision-making processes varies in terms of time and effort, causing the boundary of the decision space to change and resulting in inconsistent decision processes. Although most organizations aspire to achieve a methodical and rational approach in their business processes, their set of preferences is not continuous and complete, thus violating the axioms of the rational model. The set is essentially a loose collection of ideas where the preferences are discovered through action rather than active deliberation and calculation.

The decision-making process at the personal level differs from that made in organizational contexts. While personal decision-making is based on individual preferences and values, organizational decision-making involves a more complex and structured approach. Therefore, to understand the technical decision-making process in industries, it is imperative to study and analyze the decision-making process in the organizational context. Unlike individuals as actors in a social group, organizations have a rigid hierarchical structure where organizational agents play specific roles in achieving organizational goals. Each role has specific functions and responsibilities contributing towards the organizational goals.

2.4.1 Strategic, Tactical, and Operational Decisions

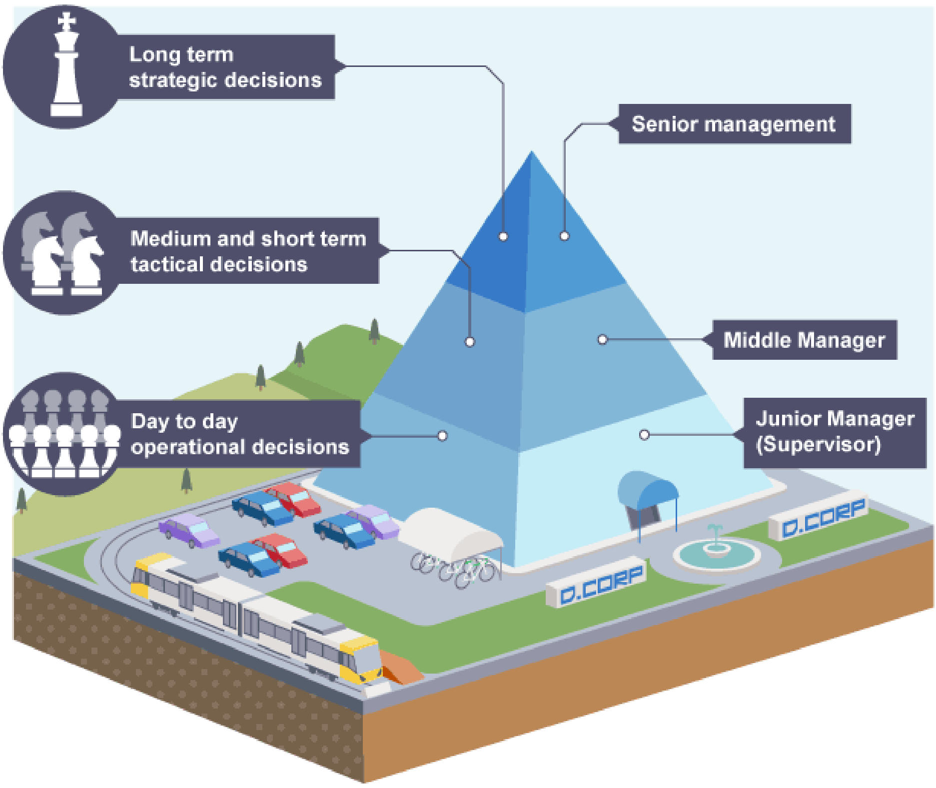

Figure 8: Visualization of strategic, tactical, and operational decisions in organizations (British Broadcasting Company, n.d.)

Different hierarchical levels in an organization are responsible for different decision objectives. Top management is expected to make decisions that define the direction of the organization, while lower-level executives make decisions for the daily operation of the organization. Organizational decisions can be classified into three levels: strategic, tactical, and operational, with the allocation of decision-making responsibilities contingent upon the hierarchical structure of the organization.

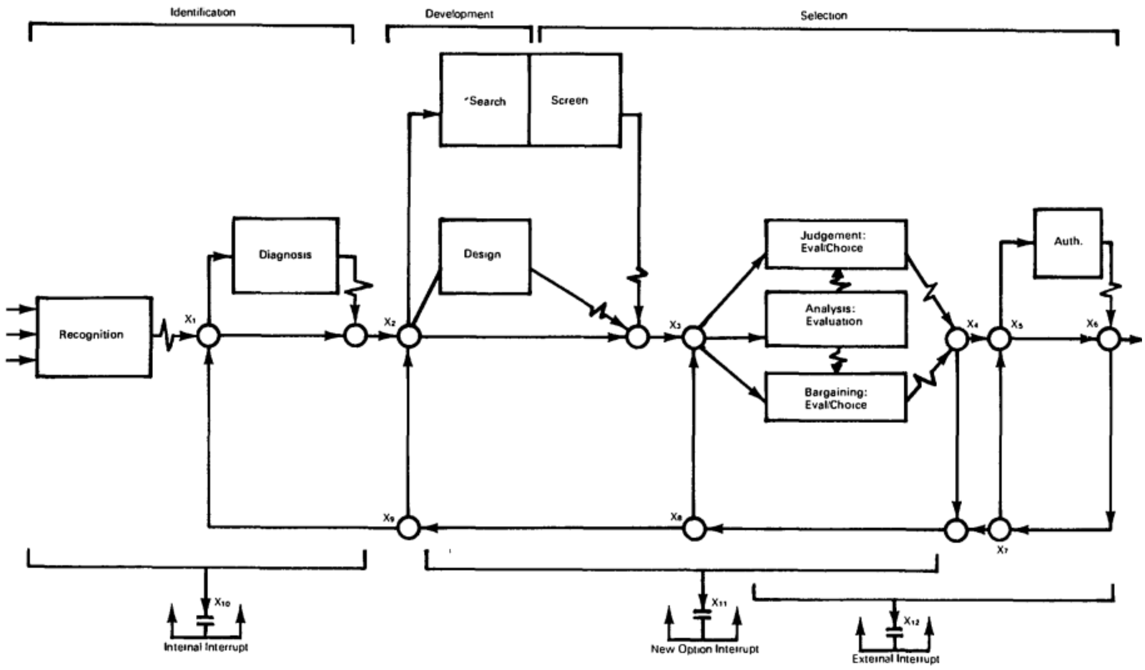

Figure 9: A general model of a strategic decision process (Mintzberg, Raisinghani, & Théorêt, 1976)

Strategic decisions are high-level decisions made by an organization to define its long-term plans. These decisions, made by top management, are infrequent but critical in shaping the organization's course. Examples of strategic decisions include introducing a new product or service, opening a new manufacturing plant, expanding operations into a new market, forming strategic alliances, and becoming a publicly listed company (Alexander, 1985; Eisenhardt, 1989). Strategic decision-making in organizations is akin to political systems, where management executives have partially conflicting objectives and the decision processes are heavily interwoven between bounded rationality and the political power plays of decision-makers (Eisenhardt & Zbaracki, 1992). Bounded rationality introduces cognitive and social biases into strategic decision-making processes, such as overconfidence, representativeness, groupthink, and illusion of control (Busenitz & Barney, 1997; Schweiger et al., 1986). At the surface level, the strategic decision-making process can appear highly unstructured (Mintzberg et al., 1976). However, Mintzberg et al (1976) discovered that it is not and tends to follow three basic phases: identification of opportunities, problems, and crises; development of solutions or elaboration of opportunities; and selection of decisions (Figure 7). These phases contain various steps such as recognition, diagnosis, design, and bargaining. The steps are not fixed to a particular sequence but can occur in any order depending on the context of the strategic decision. Successful implementation of strategic decisions heavily depends on the effectiveness of tactical and operational decision-making processes.

Tactical decisions are intermediate-level organizational decisions. This decision level describes action plans, policies, and procedures (Harrington & Ottenbacher, 2009), as compared to operational decisions, which are the lowest-level decision stage, that see to the daily operations in functional areas of the organizations, where the decisions are mostly routine and repetitive (Hitt, Ireland, & Hoskisson, 2012). For example, tactical decisions in the logistics industry prescribe material flow management policies, while operational decisions set the scheduling operations for the delivery of final products to customers (G. Schmidt & Wilhelm, 2000). In supply chain management, tactical decision-makers deal with location-inventory-routing planning, while low-level executives focus on operational decisions such as operative order planning, supply chain monitoring, and reconfiguration of delivery routes in case of operative disruptions (Ivanov, 2010). In the field of operations management, a multitude of decision analysis methods, such as optimization and simulation, are prescribed to ensure the efficiency and effectiveness of decision processes at these levels. In healthcare management, for instance, discrete event simulation models, which mimic the dynamic behavior of a process evolving over time, can be used to solve tactical decisions such as patient flow planning and staff scheduling (Kolker, 2011).

Understanding the different decision levels helps frame the landscape of the decision-making process in organizations. Business processes, such as product development, manufacturing, logistics, and marketing, have varying degrees of decision levels. The decision levels determine the decision-making process actors and methods. For example, the manufacturing process involves many tactical and operational decisions. The decision-makers are generally low-level executives who rely on decision analysis methods to achieve production requirements at the strategic level.

Organizational decision-making can generally be viewed in two styles: decision as rational choice and decision-making through rule-following. Decisions as rational choices typically follow the path set by the rational model, where decision-makers pursue logic and rationality to evaluate and attain the best alternatives. Decision-making through rule-following, on the other hand, relies on decision-makers cognition and social awareness by following rules and fulfilling roles defined by the organizations (Luoma, 2016; March, 2002; Zhou, 2002).

2.4.2 Decision as Rational Choice

As discussed previously, decision theory scholars have long agreed that perfect knowledge and cognitive computing power are required to process a near-infinite number of alternatives and their consequences are impractical and impossible to achieve. However, organizations still regard decisions as rational choice as imperative and it is in their best interest not to rely on intuitions, which can be susceptible to bias. Organizations strive to evaluate their alternatives systematically and rationally, by obtaining as much information about the problem as possible and employing formal decision-making techniques to evaluate and rank the best set of alternatives.

The use of decision analysis, as explained in Section 2.2.2, is pervasive in organizations, where the role of decision analysis is not to make the final decisions but to assist decision-makers in making better decisions. Decision analysis provides the mechanism to dissect a decision problem into a set of smaller problems, analyze the information objectively, and propose a set of alternatives from which decision-makers may choose (Wright & Goodwin, 2009). It simplifies real-world problems, where the optimized models can be used as approximations (Simon, 1972). As an example, Du Pont used influence diagrams and Monte Carlo techniques to increase the effectiveness of their strategic decision-making. The analysis used multiple inputs – such as competitors' strategies, market share, and market size – which helped Du Pont develop a business strategy that enhanced its business value by USD 175 million (Krumm & Rolle, 1992). In another example, ICI Americas used a decision tree tool to select research and development projects from 53 new product ideas. Using a variety of criteria – such as technical risk, time to develop, and sales growth potential – they managed to reduce uncertainty in information, work with a limited amount of data, and produce satisfying alternatives (Hess, 1993).

Although a decision made through rational choice may yield better results due to its systematic approach, the labor-intensive process would be tedious for simple and routine decisions. Therefore, some organizations provide their decision-makers with rules or guidelines when making decisions.

2.4.3 Decision as Rule-following

Decisions in organizations are mostly made based on rules defined by the organizations themselves or by international regulatory bodies, such as norms, operating procedures, guidelines, and standards. Organizations develop these rules through formal learning, experiences, repeated exposure to similar events, and interactions within the organization and with other organizations (Chaiken & Trope, 1999; Luoma, 2016; Zhou, 2002).

In decision situations of rising complexity, organizations tend to adopt simple rules and rely on predictable behaviors instead of increasing their efforts on rational decision-making. If the rational model follows the logic of optimization, where decisions are made based on the optimization and maximization of outcomes, rule-following decision-making is based on the logic of appropriateness (Zhou, 2002). In the logic of appropriateness, decision-makers identify the social role they are required to play and match appropriate rules to the decision space (March & Olsen, 1989).). It has been observed that organizations prioritize the appropriateness of procedures over maximizing decision outputs (Carroll, 1994; Dobbin, 1994). March (2002) states that three factors define rule-following decision-making: situation, identity, and matching. First, decision-makers observe the decision space and make sense of the situation. Second, they identify their specific role and identity within their organization. And finally, based on the recognition of their identity, they match and apply appropriate rules to the decision context.

Rule-following decision-making behavior in organizations exists on both micro and macro levels (Zhou, 2002). Zhou states that at the micro and individual level, decision-makers and their decision-making tendencies are shaped by social categorization, based on their education and social settings. Through professional training and practices, employees are taught and imbued with specific roles and social perceptions that they are expected to embody. The biases of these individuals are affected by the social constructs of the organization. On the other hand, at the macro and institutional level, Zhou (2002) describes that organizational decision-making is shaped by external influences, such as regulations, laws, and cultures. Organizations tend to adopt successful decision-making processes from other organizations. The larger the stakes and the higher the uncertainty, the more organizations tend to rely on rules rather than to rationally analyze the decisions (Zhou, 2002). Organizations apply rule-following behaviors in a variety of decision situations, such as operational requirements to increase the efficiency of bureaucracy and systematic evaluations of new opportunities.

Conventionally, organizations prescribe rules and guidelines to decision-makers to increase organizational efficiency by optimizing the performance of decision-making, especially in routine situations. Rule-following decision-making reduces information processing, eliminates alternative searching, and emphasizes interpretation of the decision context instead of consequential calculation (Zhou, 2002). This leads to more efficient and reliable decision-making in routine situations where the rules closely match the decision context. For example, clinical prediction rules are used in the medical industry to make a diagnosis or predict an outcome using clinical findings such as historical data, physical examinations, and test results (Laupacis, Sekar, & Stiell, 1997; Wasson, Sox, Neff, & Goldman, 1985). A study by Reilly and Evans (2006) showed that clinical prediction rules are a powerful tool to improve clinical decision-making. They also observed that if physicians intentionally overrule the decision rules, their decision-making efficiency is reduced. Furthermore, decision rules increase organizational performance when applied correctly. In complex decision-making environments, decision-makers are expected to combine multiple environmental factors, master the correct rules, and explore experimental strategies to yield the best composite rules (R. Wood, Bandura, & Bailey, 1990).

Modeling organizational decision-making processes increases the efficiency and effectiveness of the decision process by enhancing the speed and accuracy of decision-making calculations. However, it may limit the emergence of creative solutions and force organizational actors into narrow problem framings, thus limiting their ability to recognize change (Luoma, 2016). Nevertheless, rule-following decision-making does not have to be a rigid, automated process.

Decision-makers require a high level of critical thinking to select, combine, exploit, or neglect rules. Highly analytical decision-makers use decision rules to improve their innovation.

Outside of the conventional usage of decision rules, entrepreneurs have been using the rules to systematically evaluate opportunities and explore new inventions. Routines and rules are used in organizations during the innovation process to ensure the appropriate allocation of R&D resources and stabilize innovation activities (Zhou, 2002). Wood and Williams (2014) state that organizations with an entrepreneurial spirit consistently use decision rules regarding opportunity novelty, resource efficiency, and worst-case scenarios to evaluate opportunities. Organizations use their deep knowledge regarding opportunity technology and opportunity markets to create demand-side rules to judge the potential of the opportunity. Using resource efficiency as a supply-side rule, organizations can judge the attractiveness of an opportunity by evaluating the resources required to pursue it. Organizations often ask themselves what the worst-case scenario could be if the opportunity under consideration is pursued. Entrepreneurs apply the supply-demand nexus rule to evaluate the relationship between opportunity novelty and resource efficiency. The relationship is carefully considered to avoid the severe effects of a worst-case scenario (M. S. Wood & Williams, 2014).

The decision rules are highly subject to the heuristics and biases of the creators and the users of the rules. The creators draw from their formal knowledge and bias-laden experiences and observations to create the rules. The rational model is not respected during the creation of the rules because none of the organizations has complete knowledge of the environment, nor do they have enough computational power to produce a consistent and rational set of rules. Decision-makers are also expected to rely on their cognitions, which are prone to biases, to evaluate the decision situations, recall, select, and combine the rules, and derive the appropriate decision. This contradicts decision-making as a rational choice.

The decision-making process in organizations is complicated because it is tightly intertwined between decision-making as a rational choice and rule-following. Organizations pursue the rational model of decision-making, which is highly logical but resource-intensive, but at the same time use decision rules to balance the rationality and practicality of the decision process, which is prone to heuristics and biases. The organizational decision-making landscape is further complicated by the number of participants generally needed in the decision process. It is reasonable to assume there are multiple actors in organizational decision-making processes, ranging from those who collect information, analyze alternatives and their consequences, to those who make decisions. This thus begs the question: are decisions in organizations generally made by single or multiple individuals?

2.4.4 Decision through Consensus or Single Agent

The renowned principle of Gestalt psychology, formulated by Kurt Koffka, advocates that “the whole is different than the sum of its parts” (Koffka, 1935), which is often misinterpreted as “the whole is greater than the sum of its parts” (Heider, 1977). Regardless of the interpretation, the principle affirms that a system is not merely a sum of its parts but an independent entity of its own. An organization is a system comprising its actors, infrastructures, and processes. Thus, organizational decision-making cannot be viewed simply as a summation of individual decision-making processes, but as a system of decision-making processes existing in a complex interrelation that cannot be easily untangled and reconstructed. In organizations, decisions are made by both individuals and through group consensus. Due to diversity and its complex nature in organizations, group decision-making presents its own challenges and benefits to the organizational decision-making process as a whole.

Both small and large organizations are experiencing workforce diversification, mainly due to globalization and shifting demographics. This is especially apparent in organizations with a global operational base and the formation of interdepartmental and inter-organizational alliances. Diversity in organizations can be grouped into content-related attributes – such as knowledge, skills, organizational tenure, and education level – and structure-related attributes – for instance, culture, age, social status, and gender – of the employees (Jackson, May, & Whitney, 1995). Variations in group composition impact the decision-making process in organizations, especially where decisions are made through group consensus. Some of the group properties that influence decision-making are roles, norms, status, cohesiveness, and diversity (Robbins & Judge, 2001).

Different members assume various roles – such as information seeker, elaborator, coordinator, and procedural technician -- in group decision-making (Benne & Sheats, 2010). Benne and Sheats explain that the information seeker searches for facts and information and provides clarification of the factual adequacy of the information, while the elaborator explains alternatives suggested by group members in terms of examples and deduces the consequences of the alternatives. Meanwhile, a coordinator clarifies relationships between ideas and recommendations and tries to coordinate the activities of the team members, and the procedural technician performs routine tasks to expedite the decision process. Each team member has a certain perception of the role assigned to them, while other team members may have differing expectations of such roles. However, roles are generally assigned based on stereotypes, instead of actual underlying attributes of each team member (Jackson et al., 1995). This may lead to inappropriate assignment of responsibilities and mismanaged performance expectations. When role expectations are mutually contradictory, role conflict may cause stress in the group and impact its decision-making performance (Robbins & Judge, 2001).

Most groups have established norms, or acceptable standards of behavior, agreed upon by their members, on what to do and what not to do (Forsyth, 1990; Robbins & Judge, 2001). Robbins and Judge further decompose the norm into a performance norm (outlining expectations of work output), appearance norm (stipulating dress code and behavioral conducts), social arrangement norm (specifying requirements of group activities), and resource allocation norm (defining the assignment of jobs and distribution of resources). The core concept of establishing norms is the requirement of conformity imposed on all group members. This may lead to undesirable social biases such as groupthink and herd behavior (Banerjee, 1992; Janis, 1971).

Status exists in every society and defines the social rank given to group members. According to status characteristics theory, status is derived from a person’s power over group resources, their ability to contribute to the group’s success, and their desirable personal characteristics – such as good looks, high intelligence, and pleasant personality (Berger, 1977). Status disparity shifts the dynamic of group decision-making, particularly toward high-status members. In stressful situations, team decisions gravitate around high-status members due to their perceived competency (Salas, 1991). The disparity also inhibits diversity of ideas, as high-status members become more authoritative, and lower-status members tend to participate less actively and are generally less likely to share information (Chattopadhyay, 2014; Eisenhardt, 1989; Salas, 1991; Silver, Cohen, & Crutchfield, 1994). However, high status can insulate a team member from the pressure to conform to the group's norms (Harvey & Consalvi, 1960; Robbins & Judge, 2001). High-status individuals are not only given more freedom to deviate from norms but are also better able to disregard the conformity of norms than lower-status members (Hackman, 1992; Harvey & Consalvi, 1960). Furthermore, in normal situations, the majority faction can exert influence on the minority group. However, a majority faction of low-status members does not yield such influence. Dovidio and Gaertner found that high-status team members continue to discount the competency of the low-status faction even when outnumbered (Dovidio & Gaertner, 1983).

Group cohesion, or bonds between team members, affects group productivity and decision quality (Forsyth, 1990; Robbins & Judge, 2001). Group cohesion exemplifies the Gestalt principle, stating that a group is a whole independent entity, not necessarily greater but certainly different than the sum of its members. Mullen and Copper (1994) discovered that cohesiveness is a double-edged sword for group performance. It impairs decision-making when motivated by interpersonal attraction or group pride but enhances decision-making if operationalized as a commitment to the task (Mullen & Copper, 1994). The commitment to achieving successful task performance encourages team members to cooperate and regulate their actions toward achieving that goal. The group cohesion-productivity relationship is also highly dependent on the group's performance norm. If the performance norm – such as standards for work quality, work output, and cooperation – is low, even with high cohesiveness, productivity will be low. However, if the performance norm is high and cohesiveness is low, productivity increases (Mullen & Copper, 1994).

Diversity in group composition affects group decision-making performance. Heterogeneous teams make better decisions because they possess diverse task-related attributes, such as knowledge, skills, and abilities. However, the diversity of relation-oriented attributes — such as social status, attitudes, and values – may cause conflict in the team. Personal affiliations, less satisfaction, self-serving behavior, and group politics become common occurrences in the team (Jackson et al., 1995; Staples & Zhao, 2006). George and Chattopadhyay (2008) compiled studies on the effects of group diversity in decision-making and summarized that due to a diverse wealth of knowledge and skills, diversity may increase group decision-making performance if members can work together. However, they also state that diversity can negatively influence group member interactions, cause low effectiveness in sharing and processing information within the group, and low commitment to group decisions. This is due to the similarity attraction paradigm, where members of dissimilar categories have high motivation to avoid social interaction with each other and are less likely to share information (Byrne, 1971).

It is challenging to ascertain whether group decision-making is superior or inferior to individual decision-making. On one hand, group decision-making is advantageous as it encompasses more information due to the diverse composition of the group, facilitates a critical analysis of the information, yields more alternatives, and fosters commitment to group decisions (Leavitt & Bahrami, 1988; Robbins & Judge, 2001). On the other hand, group decision-making can be perceived as unattractive since it is time-consuming. Moreover, discussions and group decisions can be dominated by high-status members, with the roles and responsibilities of team members remaining ambiguous at best (Robbins & Judge, 2001).

Based on the review of decision-making literature thus far, several conclusions can be delineated and encapsulated as follows:

1. Decision theory is predominantly characterized by two decision models: rational and boundedly-rational (or behavioral) models. The rational model posits that decision-makers aim to maximize their outputs and can consistently delineate their preferences. Conversely, the behavioral model suggests that decision-makers are boundedly rational agents and, therefore, rely on heuristics and biases to render judgments.

2. Decision-making context can be divided into two: personal and organizational contexts. Personal decisions are made daily, encompassing highly dynamic yet straightforward decision scenarios. Conversely, organizations embody a rigid social structure, mandate structured processes, and engage in more routine yet highly intricate decision-making.
3. Two distinct decision types exist, individual and group decisions. Individuals make decisions based on their self-interest and are typically less susceptible to social influences during the decision process. Group dynamics, conversely, play a significant role in group decisions. The status of group members, cultural diversity within the group, and member roles can profoundly influence the outcomes of the decision-making process.
4. When a decision model is superimposed onto the decision context of organizations, two decision styles emerge: decision as a rational choice and decision as rule-following. Decision as a rational choice illustrates how organizations are gravitating towards rational models and necessitate the employment of decision analysis to augment rationality in decision-making. However, as the rational decision-making process demands substantial computational and organizational resources, organizations prescribe decision rules, which are subjected to the biases of rule makers, for the employees to adhere to.

The literature on decision-making is extensive, and the landscape of decision theory is vast in scope. It transcends many disciplines and extends over a hundred years of research. Even when the focus is on organizational decision-making, the available literature is abundant. Decisions in organizations vary from strategic decisions. So, no single decision-making model can encompass all decision scenarios within organizations. Therefore, limiting the research scope of this thesis to a specific decision scenario was important.

2.5 Technical Decision-making in Product Development

Technical decision-making in the product development process is the focus of this research. Strategic and tactical decisions converge during product development, where business decisions transform into inputs for largely systematic technical processes. The presence of unknown variables and unverified information during the decision-making process in the product development phase is a common occurrence. This situation may compel decision-makers to rely on their instincts and heuristics when making technical decisions, even though a high degree of rationality and objectivity is expected. This chapter will delve deeply into the technical decision-making process within the product development process.

2.5.1 Product Development Process

Technical processes in the industry are dominated by rational analysis and rule-following behaviors, particularly in the engineering product development process, where the process is well-defined by international standards, industry-wide norms, and organizational best practices. The product development processes are meticulously outlined to ensure high product quality while reducing its technical, commercial, and liability risks.

Many product development models exist, such as waterfall, iterative, stage-gate, spiral, design for Six Sigma, v-model, lean, and agile. Most of these models can be grouped into three strategies: once-through, incremental, and evolutionary (ISO/IEC/IEEE, 2018). The once-through strategy is a linear process where the development process, for example, user requirements, design and development, verification, and validation processes, are only performed once and done in sequence. The incremental strategy, on the other hand, defines user requirements upfront, and then performs the rest of the development process in builds. Each build develops the planned requirements in stages until the product is feature-complete. Finally, the evolutionary strategy also develops the system in builds. In the evolutionary strategy, the user requirements are neither frozen nor defined upfront. This approach allows for flexibility in product development by monitoring user feedback and changes in technology and adapting the product accordingly.

From the various product development models, this chapter reviews the waterfall, v-model, and Agile Development processes due to their relative importance in the industry.

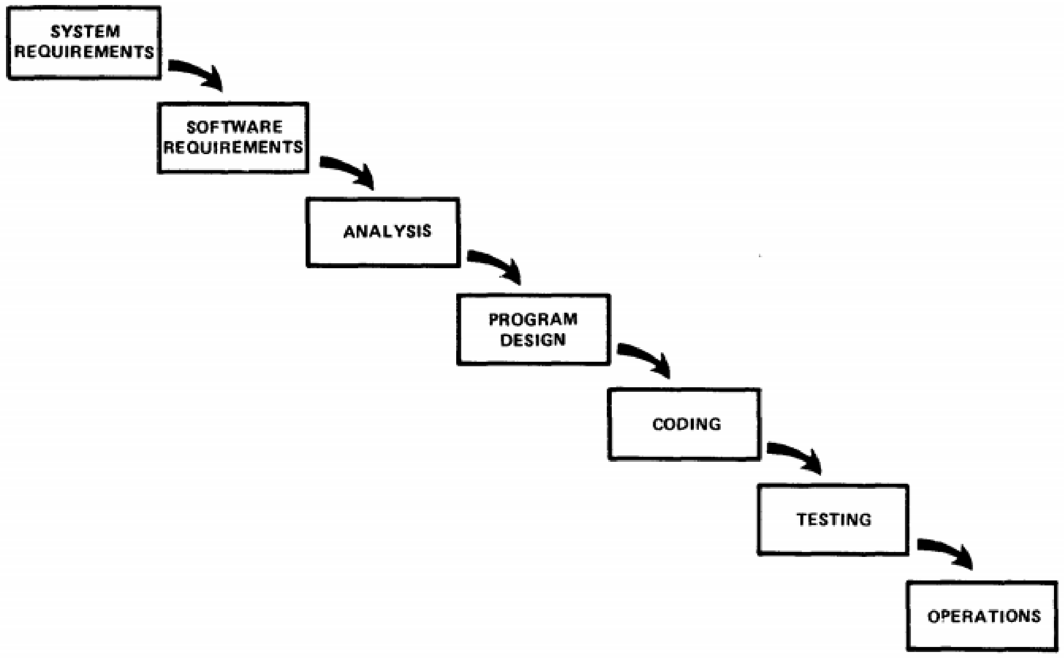

Figure 10: Waterfall Model (Royce, 1970)

The Waterfall model was first introduced to manage large software development (Royce, 1970). It is a quintessential once-through strategy in which the phase of product development proceeds in sequence, from requirements analysis to the deployment phase (Figure 10). The phases must be executed one at a time and largely resemble the widely used stage-gate model (Figure 11). The linear nature of the model has its advantages, as system requirements must be clarified in the initial phase of product development and the resources needed to execute the development cycle can be planned ahead, in which each phase is properly documented for quality control (Alshamrani & Abdullah, 2015; Balaji & Murugaiyan, 2012). However, the linearity of the process can also be the root cause of its many disadvantages. The integration and validation of the overall system at the end of the product development cycle can lead to unexpected quality issues, high development cost, and unmanageable project schedule (Jones, 1996; Royce, 1970). Furthermore, the waterfall model is also ill-suited to cope with the changing requirements of customers, leading to failures in adequately addressing customers' current needs (Larman, 2004; Petersen, Wohlin, & Baca, 2009).

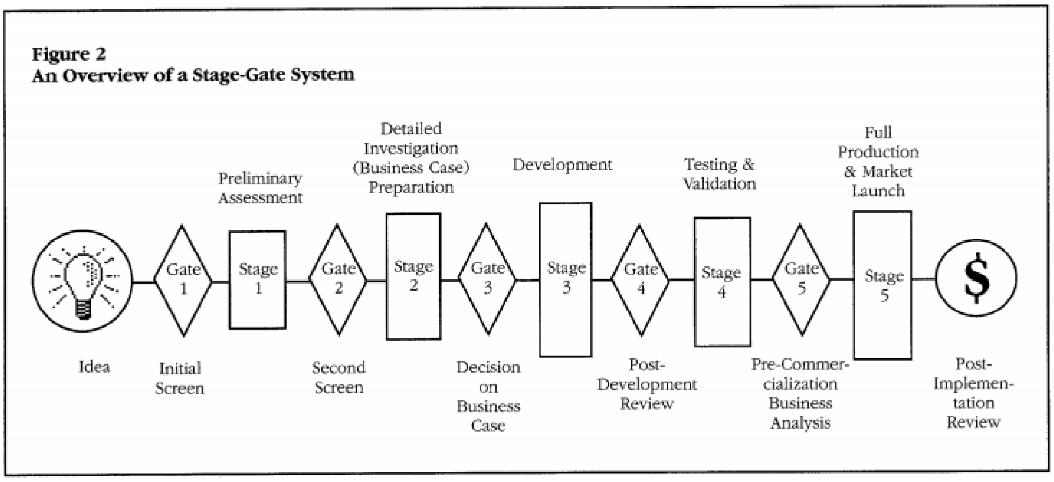

Figure 11: Stage-Gate Model (Cooper, 1990)

Based on the shortcomings of the waterfall model, the V-model was developed to introduce a flexible procedural process in the product development of mechatronic system (VDI, 2004) (Figure 12).

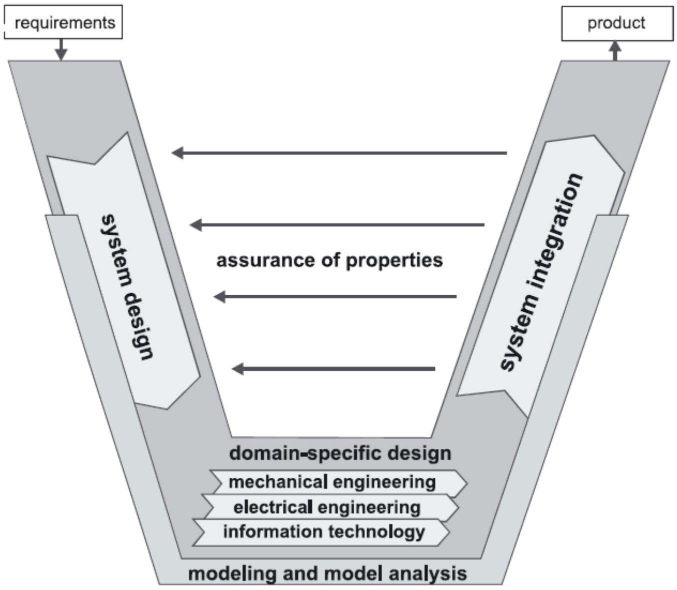

Figure 12: V-Model (VDI, 2004)

The V-model is rooted in the linear approach of the waterfall model but incorporates iterative development cycles, where a product is developed and tested within both micro and macro cycles. There are two sides to the V-model; the left side describes the decomposition of requirements and design solution, while the right side illustrates the incremental steps of design verification (Figure 12). The macro-cycle entails design and testing on the system level. The V-model commences with system design where customer requirements are analyzed to develop cross-domain system-level solutions and later broken down into requirements of domain-specific solution elements. The micro-cycles, at the base of the V, consist of a detailed solution development process where the decomposed requirements are designed and tested iteratively by each domain in parallel. The V-model closes the development loop by ensuring the domain-specific and system-level development are tested incrementally according to their integration levels. Due to its systematic approach to managing large projects and its reliance on good documentation, the V-model has found its place in many industries including medical device, space, and automotive industries (Braun et al., 2014; Mc Hugh, Cawley, McCaffcry, Richardson, & Wang, 2013; Mccaffery, Mcfall, Donnelly, Wilkie, & Sterritt, 2005; Yadav & Goel, 2008). However, as a project enlarges, the assurance of product consistency through the V-model approach escalates in complexity (Rausch, Bartelt, Ternité, & Kuhrmann, 2005).

The inception of the Agile Development model stemmed from the frustration with traditional process-heavy development practices that engendered slow product development times and an inability to adapt to changes (Martin, 2002). Agile Development was founded on a set of manifesto that values “individuals and interactions over processes and tools, working software over comprehensive documentation, customer collaboration over contract negotiation and responding to change over following a plan” (Agile Alliance, 2001). The manifesto advocates iterative and evolutionary development to reduce rigidity and needless complexity while augmenting the transparency of the design process (Martin, 2002). Agile Development frameworks such as Scrum, Extreme Programming, and Dynamic Systems Development Methods were crafted based on this manifesto. An example of the Agile Development model is shown in Figure 13 which is named Scrum framework.

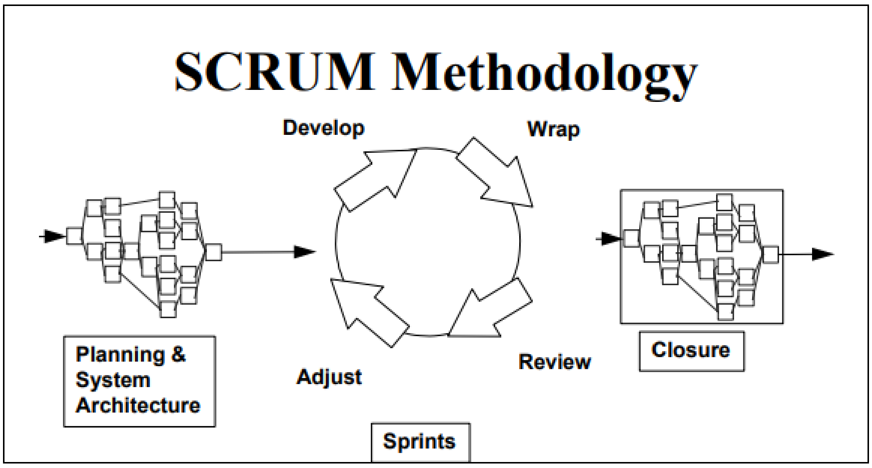

Figure 13: Agile Development: Scrum Framework (Schwaber, 1997)

The Scrum framework depends on the agility and flexibility of engineers and developers to review, develop, and test design solutions iteratively, in short burst amounts of time; this is also known as a sprint cycle. A sprint cycle normally lasts between one to four weeks. Planning and prioritization of deliverables, or user stories in Scrum lingo, are conducted using a product backlog list before sprint cycles. These processes are delegated between the ScrumMaster, product owner, and team members, to ensure that the team members can develop the required functionalities within the short sprint cycle while adhering to the high-level design of system architecture (Schwaber, 1997). The ScrumMaster is integral to the success of implementing the Scrum process. He or she facilitates the team members to produce required functionalities based on the backlog and supports the product owner in prioritizing the functionalities (Schwaber, 2004).

The benefits of agile methods are numerous. The method provides clarity of product development to the developers, project managers, and customers. Customers can monitor the real progress of the project and are provided with the flexibility to make changes to the requirements during the developmental phase (Paasivaara & Lassenius, 2006). However, according to Drury, Conboy, and Power (2012), the methods can cause the team members to focus more on tactical decisions and lose sight of overall organizational strategies to fulfill customer needs and wishes. Since the team members rely heavily on ScrumMaster for decisions, they also tend to not take ownership of such decisions. This leads to some decisions not being implemented if they are not monitored or followed up by the ScrumMaster.

Product development processes can differ between organizations as they employ development models based on their organizational culture, product types, and industry's norms and best practices. However, a general set of product development processes exists and has been outlined by the International Organization for Standardization in ISO 15288 (ISO/IEC 15288, 2005). International Council on Systems Engineering (INCOSE) further elaborates on the implementation in their Systems Engineering Body of Knowledge (Haskins, Forsberg, & Krueger, 2006).

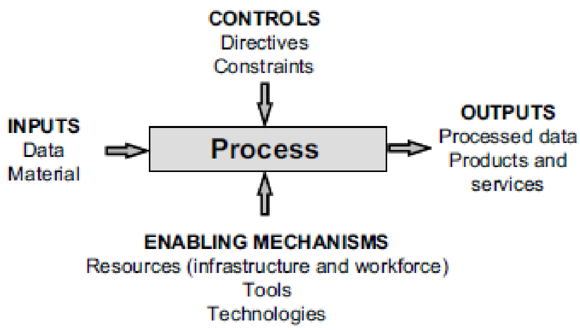

Figure 14: Inputs and outputs of a process for engineering a system (ISO/IEC/IEEE, 2012)

A process (Figure 14), as defined by ISO 24748-2, comprises a set of activities that transform inputs into a specified output. An activity entails a set of cohesive tasks that contribute to the achievement of outcomes of a process. The transformation of inputs into outputs can be affected by controls and enabling mechanisms. Controls are constraints imposed by organizational management directives or governmental regulations while enabling mechanisms are resources, tools, or technologies that facilitate the fulfillment of the process (ISO/IEC/IEEE, 2012).

ISO 15288: Systems and software engineering — System life cycle processes outline the system lifecycle of a product from an engineering point of view, starting with the conception of ideas to the product retirement. The system lifecycle (Figure 15) does not only cover technical processes, such as requirements analysis and validation, but other commercial as well as managerial processes (ISO/IEC 15288, 2005). The system lifecycle can be grouped into four major processes: agreement, project, technical, and organizational project-enabling processes.

ISO 15288 characterizes agreement processes as the establishment of agreements within and between organizations on the acquisition and supply of products and services. The acquisition process is defined as a means to acquire products and services from suppliers that can meet the organizational needs of an operational system, elements of a system required in a project, or services to support project activities. The supply process, on the other hand, is invoked to set up an agreement to supply the required products and services (Haskins et al., 2006; ISO/IEC 15288, 2005).

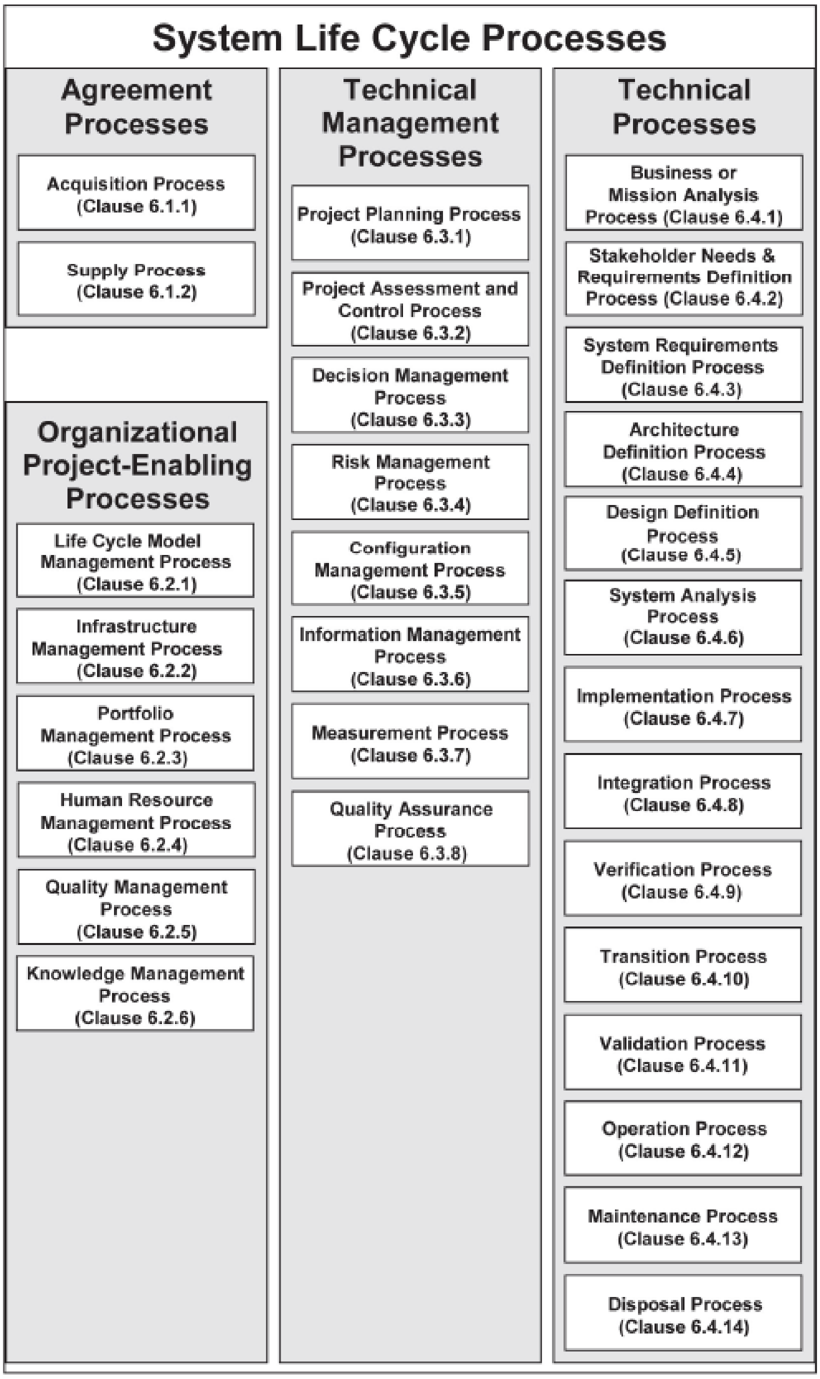

Figure 15: System life cycle processes (ISO/IEC 15288, 2005)

Organizational project-enabling processes are auxiliary activities to ensure an organization is capable of acquiring and supplying products over the entire system lifecycle. These encompass six sub-processes: life cycle management, infrastructure management, project portfolio management, knowledge management, human resource management, and quality management. Life cycle management, quality management, and portfolio management are crucial in outlining organizational product development procedures, defining business strategies, setting budgets and resources, and ensuring product and process quality throughout its lifecycle (ISO/IEC 15288, 2005). Lifecycle management is further elaborated in ISO 24748-1 and ISO 9001 (ISO/IEC/IEEE, 2018; ISO, 2008).

Technical management processes are integral to the successful implementation of a project by establishing and executing project plans, assessing the risks, achievements, and progress of the plans, and controlling the execution of the project until the end of the product lifecycle. There are two categories identified within technical management processes: project management and project support sub-processes (ISO). Project support sub-processes encompass many procedures that are important in product development. Two of them, decision management and risk management processes, are particularly of interest to this thesis. Technical management processes, which are normally handled by project managers, are further refined in the Project Management Body of Knowledge by the Project Management Institute (PMI) (Project Management Institute, 2017).

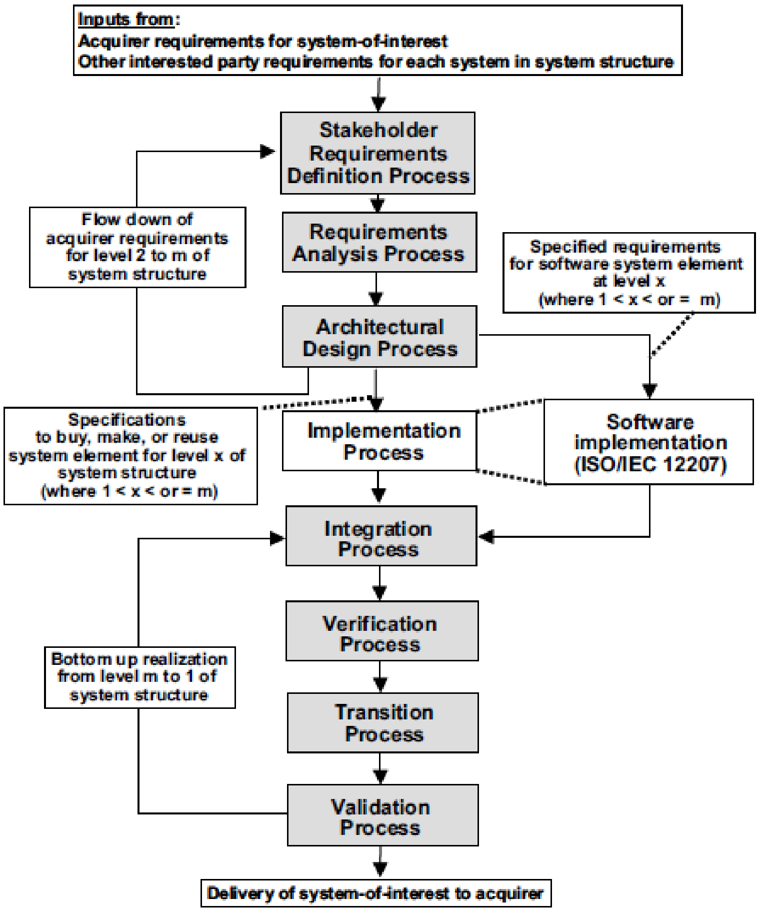

Figure 16: Application of technical management processes in product development (ISO/IEC/IEEE, 2018)

The majority of product development processes from the engineering standpoint are outlined in technical processes (Figure 16). The initiation of any product development begins with the definition of stakeholder requirements. These high-level requirements are further refined during the requirements analysis process, which sets a baseline for concept development in the architectural design process. Once the concept(s) have been selected, the architectural design is implemented by the development teams – such as mechanical design, electrical hardware, and software development – during the implementation process. Successful implementation of requirements and concept definition in product development is verified at each level of design abstraction, from the integration process through the validation process (ISO/IEC 15288, 2005). After the product has been successfully verified and approved for production, the operation, maintenance, and disposal processes follow suit, extending until the end of the product life cycle. Different industries interpret and adapt this generic product development process differently.

Depending on the industry, the ISO-proposed product development process may be modified to better fit the industry's needs. The process is defined by national agencies, interest groups, and trade associations of the industry. The automotive and space industries do not have an industry-wide organizational body that oversees a unified set of guidelines to be used by the industry players. Instead, interest groups and trade associations from the same organizations' country of origin publish their own norms. In the space industry, national and regional agencies are normally responsible for their own publication of standards and guidelines. However, medical device industry players must adhere to ISO 13485 standards, which set the quality standards for the product development process of medical devices (ISO, 2016).

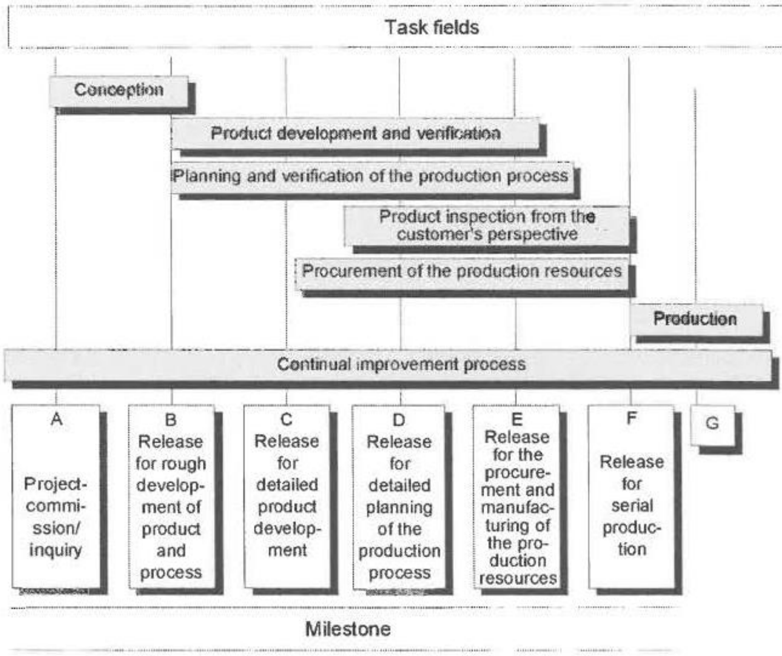

Figure 17: VDA project planning process (VDA, 1998)

Automotive industry interest groups such as Verband der Automobilindustrie (VDA) and Automotive Industry Action Group (AIAG) adopted the ISO 15288 product development process with slight deviations, possibly based on their internal interpretations of the process. As shown in Figure 15 and Figure 16, both VDA and AIAG processes have the same framework for the product development process but with different naming conventions. The process still begins with understanding market demands and customer needs, which are soon followed by product development and validation, before concluding the product development cycle with the production process (AIAG, 2008; VDA, 1998).

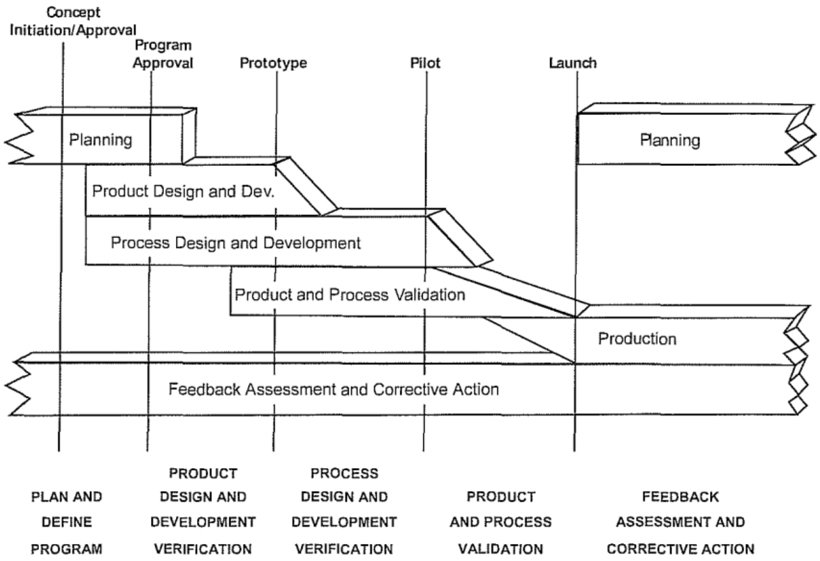

Figure 18: AIAG product quality planning (AIAG, 2008)

In the space industry, the European Space Agency (ESA) and the National Aeronautics and Space Administration (NASA) articulate their product development process in their respective standards and handbooks (ECSS, 2009a; NASA, 2007). Their product development processes closely follow the ISO 15288 process definition but with one critical difference. At the highest system level, unlike in the automotive and medical device industries, the space industry is not bound by consumer needs or market trends, but by the mission set out by the agencies. Therefore, the inputs into the stakeholder analysis process are different, but the outputs are largely the same; both industries require the definition of design goals and high-level requirements as outputs of the stakeholder analysis process (AIAG, 2008; NASA, 2007).

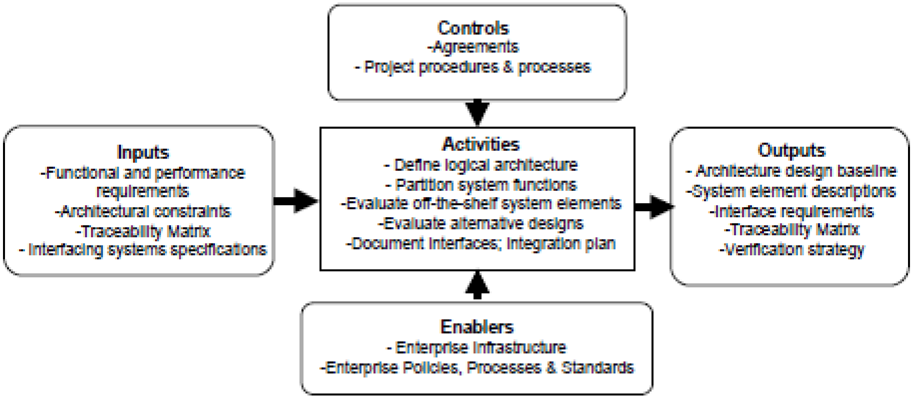

Figure 19: Architectural Design Process (Haskins et al., 2006)

During the design development stage, *Architectural design* (Figure 19), also known as system design, is a crucial process that defines a solution space that satisfies system requirements and expresses it in a set of consistent views (ISO/IEC 15288, 2005). It's a delicate balance to conceptualize a design on a system level that meets system requirements as tactical decisions, fulfills commercial objectives as strategic decisions, and ensures the technical feasibility of product development. The designs are to be selected by the product stakeholders at the end of the concept stage. ISO 42010 prescribes a unified approach to how system architectural designs are organized and expressed (ISO/IEC/IEEE, 2011). The core concept resides in the standard's establishment of a convention on the definition of architectural views. Architectural views present multiple viewpoints of the same system for product stakeholders, catering to their requirements and needs. This convention fosters the development of various modeling languages, such as SysML, UML, and IDEF, and architectural frameworks, like TOGAF, MODAF, and RM-ODP (ISO/IEC/IEEE, 2011). However, the standards do not offer guidelines on designing system solutions, nor do they propose methods to analyze and evaluate the architectural design, as required by ISO 15288.

Industry and academia provide well-defined guidelines on the architectural design process for concept generation. NASA, in its Systems Engineering Handbook, suggests a methodical approach to systems design, initially by creating a logical decomposition of system requirements and later defining design solutions based on this decomposition. Logical decomposition consists of a product breakdown structure, which delineates the product into components hierarchically, and functional analysis techniques which analyze product functions through its functional flows and interaction matrix. In defining design solutions, NASA proposes iterative design loops ensuring the consistency of basic architecture, concept of operations, and derived requirements. The concept of operations, or ConOps, is a descriptive set about the system's operation throughout its life cycle (NASA, 2007). Robert Bosch, a multinational company operating across automotive, consumer goods, industrial technology, and infrastructure sectors, publishes a product engineering handbook that includes guidelines on deriving design solutions. The approach begins by breaking down a system into individual elements and functionalities through system structuring. The relationship between the elements and their functions is then further analyzed through cause-effect relationship modeling. This graphical representation facilitates technical analysis of active parameters of the elements and their quantitative relationships, aiming to meet target parameters on a higher-level system (Robert Bosch GmbH, n.d.).

Academic researchers have ventured a different route, proposing concept generation tools and methodologies for product development. In recent years, the tilt has been towards novel approaches generating optimal concepts based on computational models and automated processes, over the "traditional" methods in the industry that still rely on engineers' creativity and collaboration. Various fuzzy set theorem-based (Hong-Zhong, Bo, & Chen, 2006; Xue & Dong, 2002; Yan et al., 2006) and computational functional analysis approaches (Bryant, McAdams, Stone, Kurtoglu, & Campbell, 2005; Liu, Bligh, & Chakrabarti, 2003), among others, have been proposed for use in the development and evaluation of design concepts. This computational approach leans towards a rational model, aiming to mitigate biases in the process (Bryant et al., 2005). Regardless of how architectural designs are generated to fulfill a set of stakeholder requirements, the design development process is particularly of interest to this research.

2.5.2 Technical Decision-Making

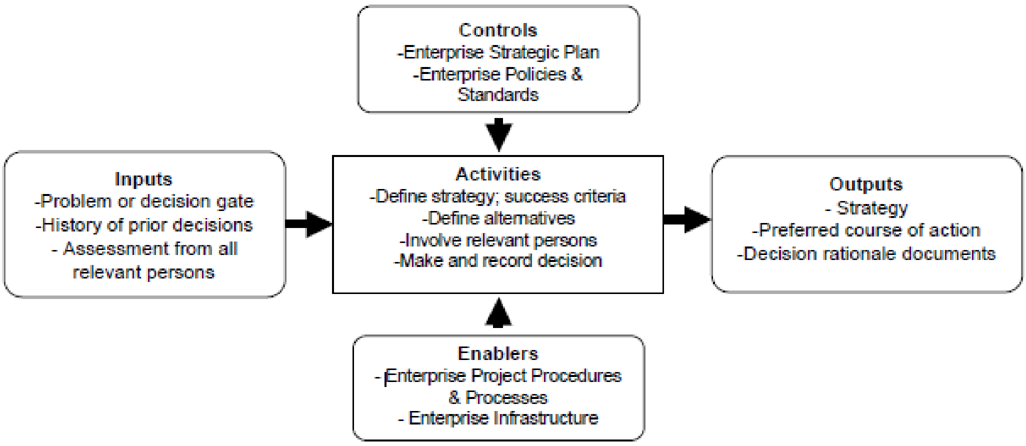

Figure 20: Decision Management Process (Haskins et al., 2006)

The objective of the architectural design process is not only to generate designs but also to facilitate decision-making during design development. However, on a larger scale, decision-making in organizations entails balancing risks and opportunities. ISO 9001, a quality management standard, mandates organizations to plan actions addressing these risks and opportunities, integrate and implement the actions, and evaluate their effectiveness. Within product development, this necessitates systematic decision management. ISO 15288 (2002) stipulates a set of requirements for the decision management process (Figure 20), providing a baseline for technical decision-making in many organizations, while ISO 24748-2 (2012) offers additional guidance on the implementation steps of these requirements:

1. Definition of decision management strategy: This strategy identifies the decision-makers, outlines decision analysis methods, prioritizes decision actions, and defines the criteria for evaluating the effectiveness of actions.
2. Identification of decision context, objectives, and decision-making team: The need and context for a decision, along with the entry and exit criteria for the decision process, are documented. Key stakeholders and their responsibilities must also be delineated to leverage their experience and knowledge.
3. Processing of decision information: Decision management strategy and measurable selection criteria must be available. Alternatives should be

identified and evaluated against the selection criteria, and their consequences to be assessed.

4. Selection and management of decisions: Preferred alternatives should be ranked quantitatively, and the rationales and assumptions behind decisions recorded. Implementation of decisions is then monitored, evaluated, and reported back to the decision stakeholders (ISO/IEC 15288, 2005).

ISO warrants that the technical decision-making process should be conducted rationally, with alternatives evaluated against measurable criteria and ranked quantitatively (ISO/IEC 15288, 2005). Depending on the decision contexts, two decision management implementations are commonly used in a product development life cycle: decision gate and decision analysis tools.

A decision gate, or phase gate, is an approval process set at the end of a project phase to ensure phase exit conditions are met and to determine if the project can progress to the next phase (Cooper, 1990; Haskins et al., 2006). The decision gate process is widely employed in the industry, with one study reporting that slightly over 60% of surveyed organizations involved in product development utilize formal stages and decision gates in some form (Griffin, 1997). These gates are typically overseen by project managers, with a cross-functional group of senior managers acting as gatekeepers. Team members are tasked with delivering work products as inputs to the decision-making process, while the gatekeepers render a go or no-go decision based on exit conditions (Grönlund, Sjödin, & Frishammar, 2010).

The exit conditions of a decision gate, akin to decision rules, vary significantly depending on the industry and the current project stage. For instance, in the concept stage of a space mission, milestone reviews are conducted to assess feasibility through the selection of system, OpsCon, and technical solutions against cost, schedule, and risk estimation (ECSS, 2009b; NASA, 2007). In the automotive sector, American automakers utilize design reviews to monitor project progress and summarize findings to management. These reviews may encompass discussions on design and functional requirements, reliability and confidence goals, and design verification progress (AIAG, 2008). Conducting design reviews aligns with the IATF 16949 requirements for management reviews at a specified phase gate. IATF 16949 is an automotive-specific quality management system derived from ISO 9001 (IATF, 2016).

Decisions made during the phase gate are generally strategic in nature, as they determine the fate of the product depending on its risk, success, and opportunities at the time of judgment. Due to the subjectivity of some inputs, decision-makers often face great difficulty in making objective judgments. Another study reports that a few variables that play important roles in the approval of a project during phase gate include the subjective probability of technical and commercial success, smoothness of technical development, and commitment of employees (Balachandra, 1984). These factors are inherently subjective and may introduce biases during the decision-making process. Therefore, while a decision gate is more suitable for project management-type decision-making scenarios, decision analysis tools are preferred for technical judgments during product engineering for their highly analytical approach.

The usage of decision analysis, explained in Section 2.2.2, in decision-making in the product development process is well-specified in the industry. International professional organizations such as PMI and INCOSE, in their body of knowledge handbooks, suggest that many decision analysis tools—for instance, multicriteria decision analysis, decision tree, sensitivity analysis, trade study, and voting system—to be used in the technical decision-making process (Haskins et al., 2006; Project Management Institute, 2017). Industry trade associations and national organizations, such as NASA, ESA, VDA, and AIAG, also propose tools like influence diagrams, cost-benefit or trade-off analysis, utility analysis, design of experiments, and failure mode and effect analysis to evaluate risks and opportunities in making technical and commercial decisions (AIAG, 2008; ECSS, 2009; NASA, 2007; VDA, 1998).

In the literature, many more decision analysis tools were developed to support decision-makers in making rational choices during product development. Some of these tools are fuzzy logic-based decision tools (Büyüközkan & Feyzıoğlu, 2004; Lin & Lee, 1991; Yan et al., 2006), multi-attribute utility analysis (Büyüközkan & Ateş, 2007; Malak et al., 2009), analytical hierarchy process (Saaty, 1990; Vaidya & Kumar, 2006), and scoring model (Hough & Ogilvie, 2005; Liberatore &

Stylianou, 1995). The decision tree has also been used in product development, not only in its original scheme (Hess, 1993), but also combined with modern computational methods to provide more robust decision analysis (Argentiero, Chin, & Beaudet, 1982; R.-Y. Chen, 2009; Tucker & Kim, 2009). Decision analysis tools are not solely rational-driven; there are a few tools that take behavioral aspects into account (Souder & Mandakovic, 1986). For example, Delphi methods systematically aggregate decision-maker's views to define consensus through a series of questionnaires (Clayton, 1997; Elwyn, 2006; Spinelli, 1983). However, academic papers on the implementation of Delphi methods and other behavioral decision analysis tools in the context of product development are scarce.

Risk management, another subset of the technical management process, oversees the architectural design process to identify, reduce, and monitor project risks (ISO/IEC 15288, 2005). The planning of risk management precedes this process; this plan must encompass risk management policies, identification of responsibilities and authorities, and resource allocation. The risk profile is managed via the Risk Management Process, in which the agreed-upon risk thresholds and conditions are utilized to monitor the risks. Risk analysis, treatment, and monitoring are conducted throughout the project lifecycle (ISO/IEC 15288, 2005). Risks with a high probability of occurrence and consequences are checked against the threshold. If a risk exceeds the threshold, alternatives for risk treatment must be investigated and implemented to manage the risk. The effectiveness of risk treatments is monitored to ensure that risks remain under control.

Based on the findings from the literature, a general model for the product development process has been developed incorporating international standards (ISO 15288) and industry-specific applications; such as the ones in automotive (AIAG, 2008; IATF, 2016; VDA, 1998), space (ECSS, 2009; NASA, 2007) and medical device (ISO, 2016; US FDA, 2018) industries. *Figure 21* summarizes the technical decision-making process during the design development stage, which served as the framework for this study.

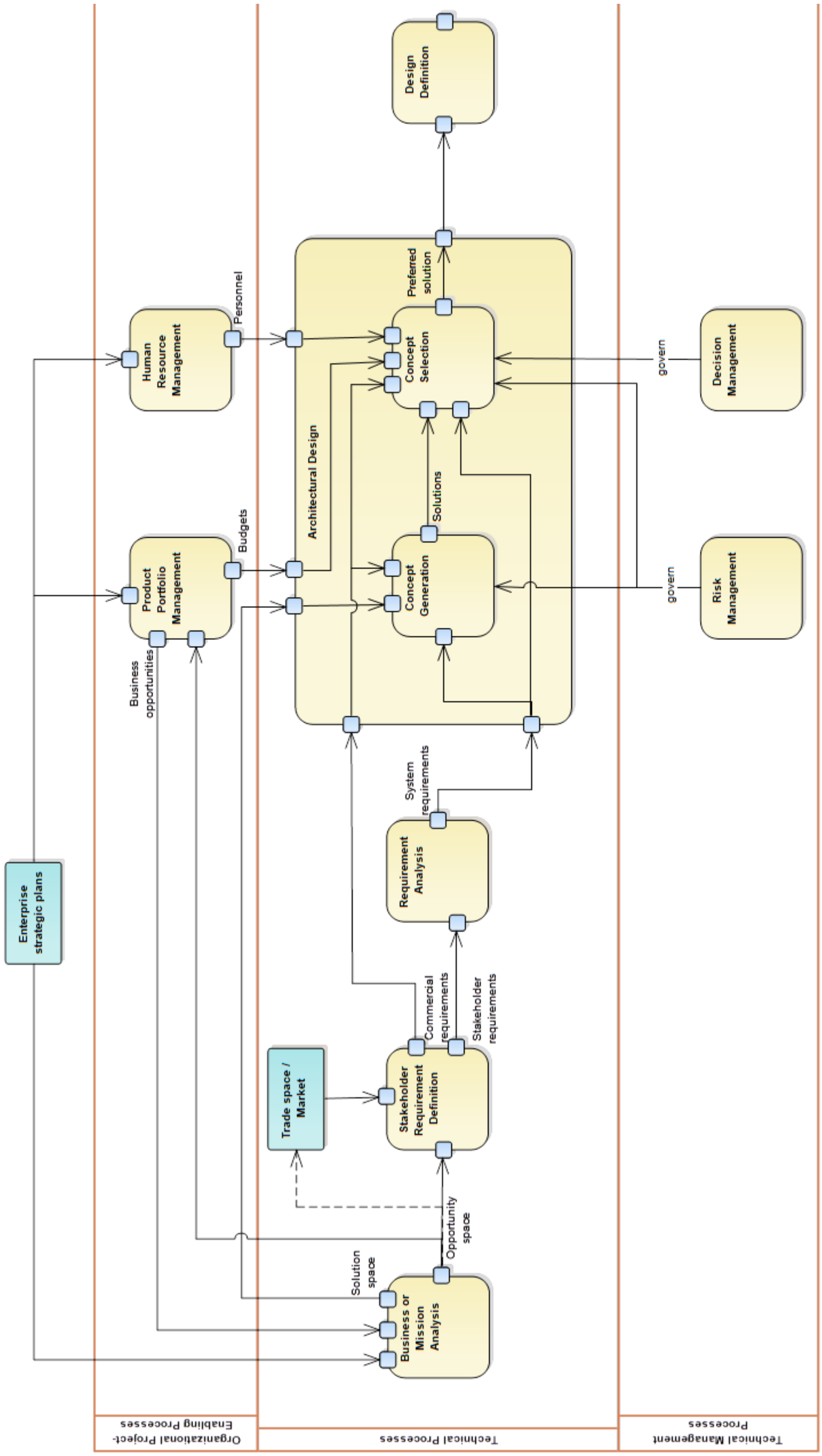

Figure 21: General model of design development phase in product development

2.5.3 Categorization of Biases in the Technical Decision-making Process

Numerous biases have been extensively studied and discussed in academia; however, identifying and analyzing relevant biases in the product development process is essential. The biases in the technical decision-making process may revolve around decision analysis, owing to the expectation of engineering organizations for technical decisions to be made rationally. Consequently, the objective of the study is to understand the manners in which biases impact decision analysis. Upon reviewing the literature, it is apparent that biases affect decision-making at three stages in the decision-making process: information processing, alternative selection, and decision revision.

Information processing biases occur when decision information is subjectively processed by the decision-maker or the group's information seeker (Kazmi, 2016). The information may be prematurely discounted, its significance downgraded or overstated, or the content of such information may be altered before it can be objectively analyzed via decision analysis. Arguably, the information might have already been tainted by previous biases even before entering the decision-making process. For instance, this might occur at its source, although it will be challenging to ascertain the extent of such bias on the integrity of the incoming information. Therefore, this thesis only considers information-processing biases that occur during the active decision-making process node, for example, anchoring, framing, confirmation, and clustering illusion.

Alternative selection biases influence the outputs of decision analysis tools. The tools analyze decision information in light of the constraints and selection criteria to objectively rank the alternatives. However, there is a tendency for decision-makers to base decisions not on the ranked alternatives, but on their instincts instead. These biases are evident in the default effect, groupthink, loss aversion, and optimism bias.

Decision-revision biases are triggered when decision-makers are prompted to reconsider their decisions upon the presentation of new information. In typical organizational decision-making processes, executives make decisions based on the limited information available to them at the time. However, the flow of information in organizations is continuous, and new information may be discovered. In cases where decision-makers have already invested money, time, and effort in making decisions, new information compels them to revise their decisions. This may allow biases to creep in during the decision revision phase. Such biases include escalation of commitment, belief revision, and choice-supportive bias.

These bias clusters discussed above are integrated with the normative technical decision-making process to generate a unified model (Figure 23) that elucidates the relationship between rational and behavioral models in the technical decision-making process.

2.6 Gap

Decision theory is a well-researched interdisciplinary topic studied by economists, sociologists, psychologists, neuroscientists, engineers, social scientists, and many others. The topic does not only span disciplines but also dates back to the 19th century. Even though the literature on the decision-making process is extensive, it is not exhaustive. So far, much of the decision-making research focuses on rational and behavioral decision models in separate studies; research on the dynamic relationship between the two in technical decision-making is sparse.

This is especially noticeable in the context of product development in engineering organizations. Most of the research in this area acknowledged the importance of rational analysis and thus proposed many more new decision analysis methods in an already crowded space (see Section 2.2.2 and 2.5.2). However not much has been done to analyze the existence and the effects of heuristics and biases that occur in this predominantly rational process. In other words, the behavioral aspects that influence technical decision-making are still understudied. As such, the current research aims to address this research gap with the following research questions.

2.7 Research Questions

Based on the literature review and discussion above, the thesis aims to address one over-arching research question, which is then broken down into four sub-research questions:

RQ 1. How do engineering organizations make technical decisions during product development?

Research Actions:

1. Examine product development processes in aerospace, automotive, and medical device companies.
2. Analyze the deviation between rational and behavioral technical decision-making.

RQ 1.1. What decision-making methodologies do engineering organizations expect for technical decisions?

Research Actions:

1. Review industry norms and standards and company guidelines to obtain an overview of the industry- and organization-specific product development processes.
2. Gather information on participants' understanding of their organization- and industry-prescribed product development processes.

RQ 1.2. What decision-making methodologies are actually employed by engineering teams for technical decisions?

Research Actions:

1. Understand the participants' approaches to making technical decisions in their daily work.
2. Observe differences between the participants' decision-making process and their organization's prescribed process.

RQ 1.3. What biases exist in the technical decision-making process?

Research Actions:

1. Review literature on human biases in the decision-making process.

2. Identify patterns or categories of human biases specific to the technical decision-making process.
3. Solicit participants’ biases in making technical decisions.

RQ 1.4. <u>To what extent do decision-makers exhibit rationality in technical decision-making?</u>

Research Actions:

1. Examine relationships between the identified biases and decision analysis in the technical decision-making process.
2. Test the significance level of the identified biases in the technical decision-making process

3 Research Methodology

The multi-disciplinary nature of organizational decision-making, ranging from the fields of psychology and sociology to operational management and engineering, requires a suitable research methodology to ensure systematic analysis of such a complex topic. In this research, both qualitative and quantitative approaches are used for different purposes and in varying degrees. This chapter outlines its conceptual framework and explains the research design used in the study.

3.1 Conceptual Framework

Scholars have researched biases in various forms and perspectives, and similarly, this thesis looks at the biases from yet another viewpoint: the biases' relationship with decision analysis in the technical decision-making process. A unified model of rational and behavioral technical decision-making has been developed as the conceptual framework of this thesis based on literature and industry norms and standards in decision-making.

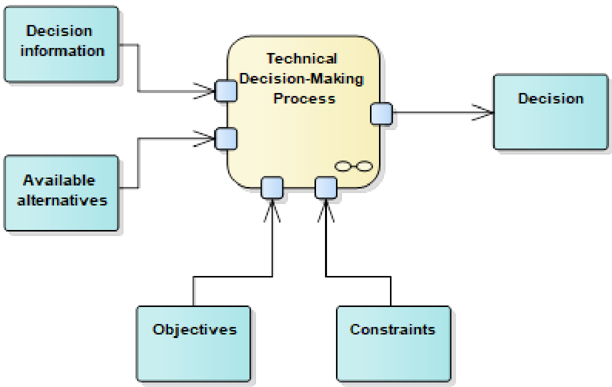

Figure 22: Normative Technical Decision-Making Process

As shown in Figure 22 above, the normative technical decision-making process was developed based on the definition of *process* found in ISO 24748-2 (Figure 14) and the decision management process outlined by ISO 15288 (Section 2.5.1). In normative technical decision-making, various inputs are fed into the process to the most optimum decision. This is done by first inputting relevant information regarding the decision context into the procedure. The potential alternatives, developed in adherence to an organization's business procedures, are then introduced into the process, where they will be evaluated and ranked. Here, decision objectives or selection criteria, defined by management, regulate the decision-making process. Also, constraints from technical, commercial, and managerial aspects would be imposed on the decision-making process. Finally, after all inputs are considered in the decision analysis the most optimum decision should be produced.

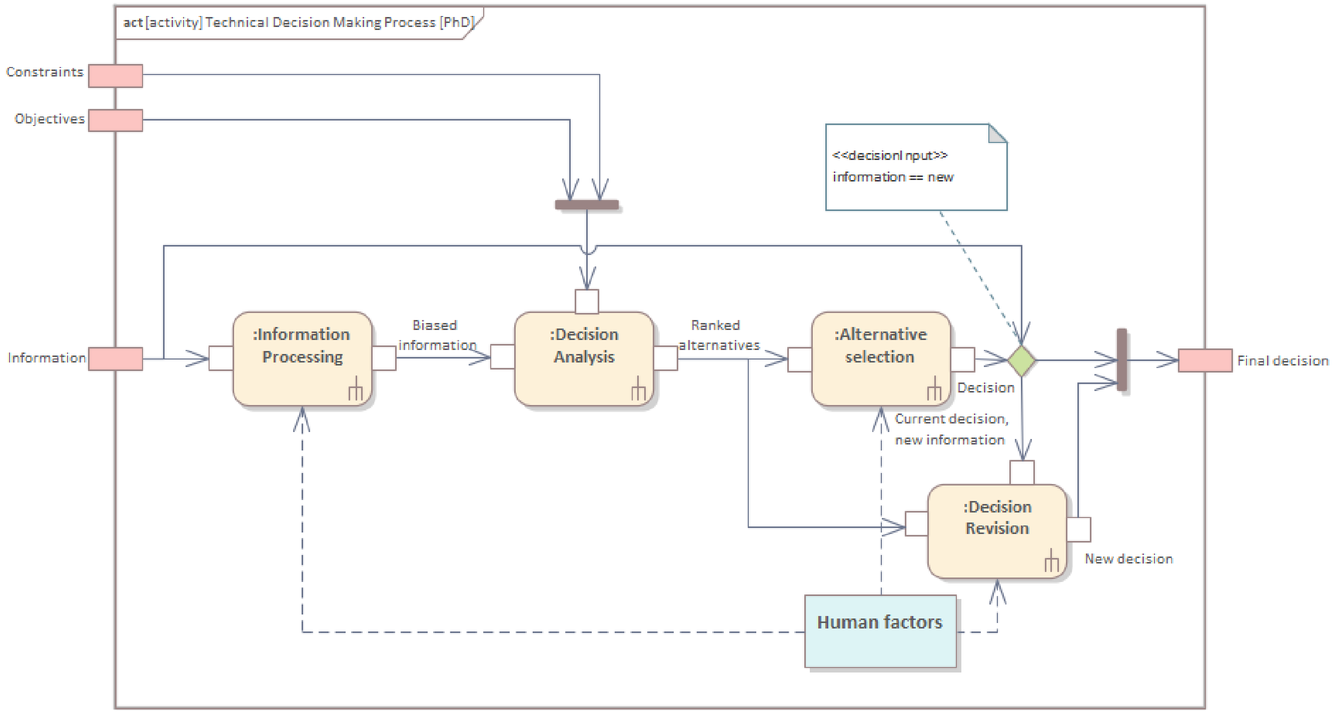

Figure 23: Unified Model of Rational and Behavioral Technical Decision-making

This model is the conceptual framework of this thesis upon which the research is based. The unified model of technical decision-making hypothesizes that biases affect the decision analysis at a specific node along the decision-making process: biases can affect the information before they are fed into the analysis, and consequently, biases can also influence the analysis and thereafter the outputs of the decision. Furthermore, if there is new information after the decisions have been made and a decision revision is required, the revision process can also be biased.

Decision-making is not only based on rationality but can also be influenced by human behavior. Since decision analysis characterizes the rational model of the technical decision-making process, human factors such as emotions and preferences represent the behavioral elements accordingly. These behavioral elements may affect the dynamics of the decision-making process and change the outcome of the decision. were then integrated with the rational model to develop the Unified Model of Technical Decision-making (Figure 23), which outlines the dynamics between rational and behavioral in the technical decision-making process.

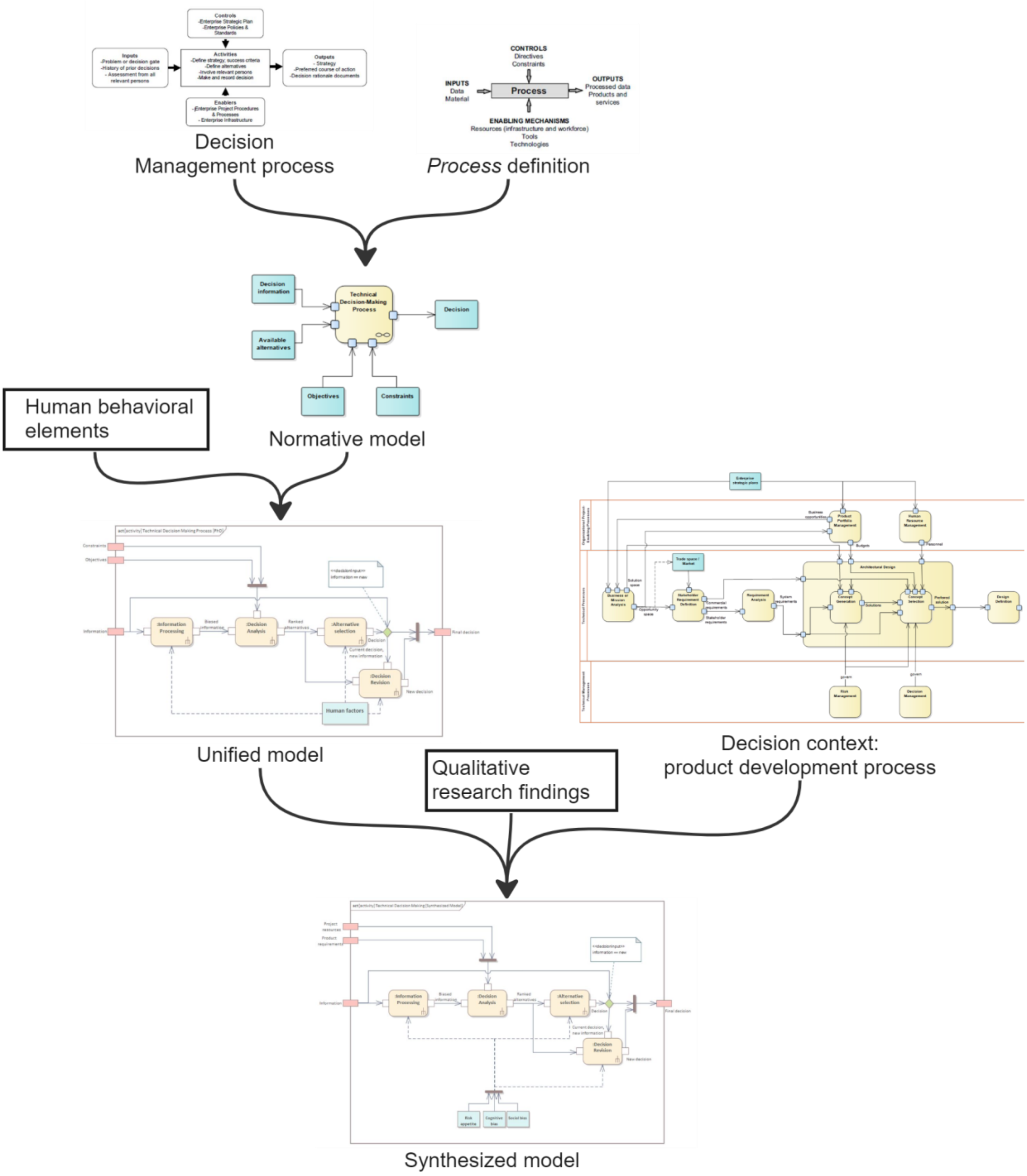

Figure 24: Development of Conceptual Framework

In Section 4.1.2 of this thesis, the Synthesized Model of Technical Decision-making in Product Development (Figure 37 & Figure 49) is introduced, developed through the integration of the unified model with the decision context and the outputs of the qualitative research. The development of the conceptual framework throughout the research is visualized in Figure 24.

3.2 Research Design: Mixed Method Strategy

Research design “refers to the way in which a research idea is transformed into a research project or plan that can then be carried out in practice by a researcher or research team” (Given, 2008, p.761). A researcher must design a set of plans that specify the strategies for how data can be gathered and analyzed based on the research questions or objectives. The selection of research design must also be done carefully, as it is dependent on the nature of the problems, the intended audiences, and the issues that are being addressed (Creswell, 2009).

The mixed method strategy combines quantitative and qualitative analyses in tandem in order to achieve a greater sum of both approaches (Creswell & Plano Clark, 2007), and it is well fitting to the direction of this research. Through the combination of both approaches, this research gains an expanded understanding of the research problems and addresses the complexity of the interdisciplinary topic at hand (Creswell, 2009). Between 2005 and 2009, at least 2524 dissertations employed mixed methods in the research design, up from only 3 between 1980 and 1984 (Haines, 2011). This is an indication that the mixed method is gaining momentum as a research method. There are six mixed-method strategies, which can be categorized into sequential and concurrent designs
Table 1).

Table 1: Mixed Method Strategies (Creswell, 2009)

Concurrent Designs	Sequential Designs
Concurrent Triangulation Strategy	Sequential Explanatory Strategy
Concurrent Embedded Strategy	Sequential Exploratory Strategy
Concurrent Transformative Strategy	Sequential Transformative Strategy

The *sequential exploratory strategy* is chosen for this research because of its layered approach that allows for the exploration of the decision-making behavior in engineering organizations through qualitative research and is supported with quantitative analysis to verify the interpretation of the qualitative discoveries. The approach taken “involves a first phase of qualitative data collection and analysis, followed by a second phase of quantitative data collection and analysis that *builds* on the results of the first qualitative phase” (Creswell, 2009, p. 211).

The literature review, as the preliminary analysis, provides a groundwork to understand historical and current research in decision-making topics. This is followed by a sequential exploratory mixed-method strategy. Qualitative approaches, through expert interviews and content analysis, are used to initially explore the organizational decision-making landscape and build a model for further quantitative analysis. Quantitative approaches, through survey research and statistical analysis, provide a supporting role to test the model for further refinement. The detailed research design can be found in (Figure 25) and explained in the following paragraphs.

The literature review in this thesis is used for two objectives. Firstly, to understand the developments in the field of organizational decision-making while making arguments for the needs of the research agenda (O’Leary, 2004). Secondly, to gather data to be used to develop a conceptual framework and decision context model.

In a thesis, a conceptual framework is crucial as it builds the foundation to chart the qualitative and quantitative research processes. The framework in this thesis, which is called the Unified Model of Rational and Behavioral Technical Decision-making (Figure 23), hypothesizes the interrelationships between biases and rational analysis in the technical decision-making process. International standards, industry norms, and guidelines were analyzed to understand the patterns of rational analysis in technical decisions in engineering organizations. Furthermore, academic journals were reviewed to explore biases in organizational decision-making and showed various clusters of biases that exist in the context of technical decision-making. The discussion of the bias clusters and their relationships with rational analysis can be found in Chapter 3.1. This information lays the foundation for the model of the conceptual framework.

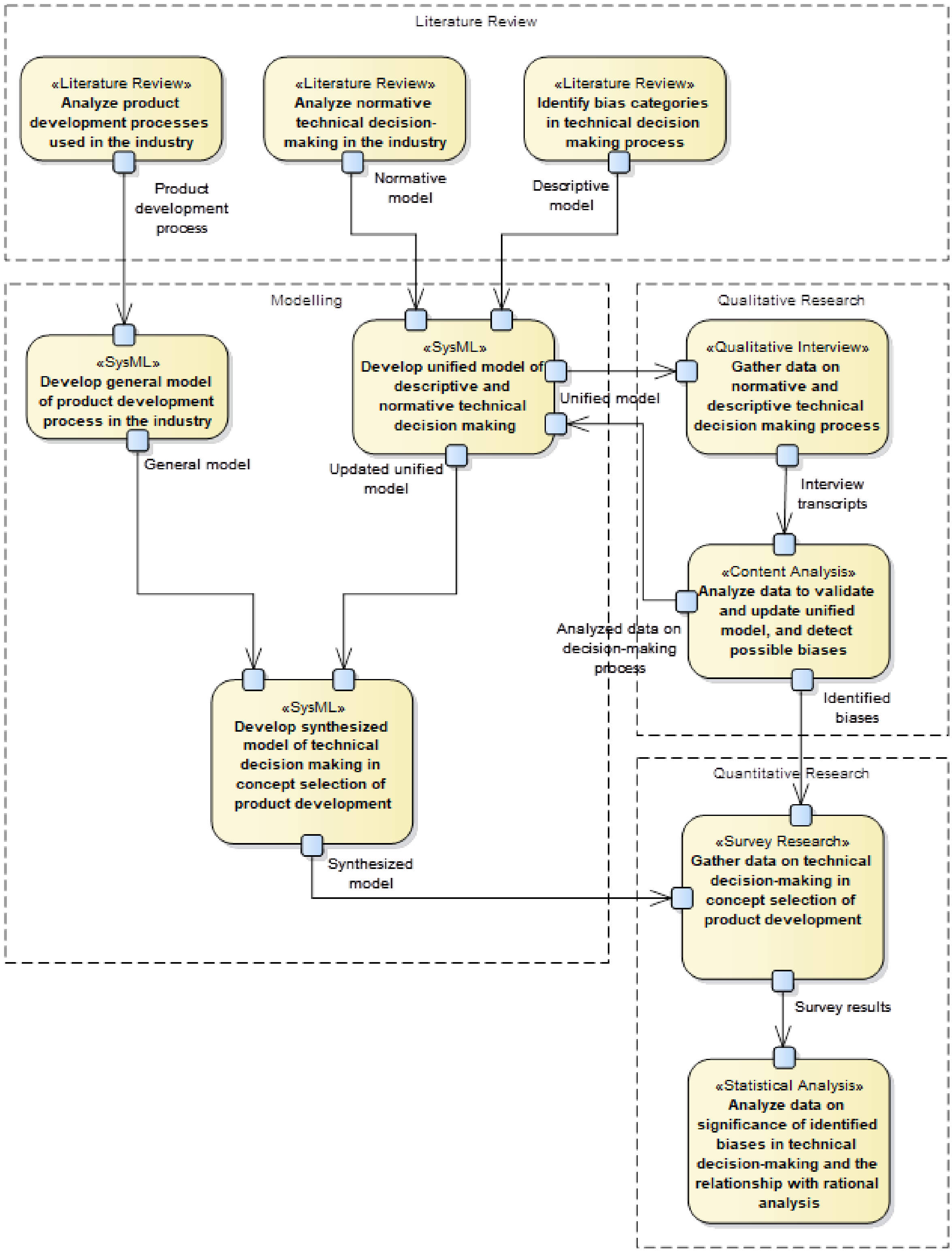

Figure 25: Research design

Decision-making cannot be studied out of context. The context has to be defined upfront so that the research directions are clear for data gathering and analysis. In this thesis, the product development process in engineering organizations is chosen as the decision context. Product development in the industry is a well-defined process in which guidelines and norms are prescribed by international bodies, trade associations, and organizations. These documents were used as the central literature for this activity, with academic journals supplementing the analysis. The findings from this activity were used to develop the decision context model also referred to as the general model of the design development phase in product development (Figure 21). The qualitative research then followed based on the critical literature review.

The qualitative research actions are to investigate the descriptive and normative decision-making in the industry and to verify the unified model (Figure 23). The data were gathered through qualitative interviews with industry experts and analyzed using content analysis. The findings from the interviews were used to verify and improve the unified model and identify specific biases that exist during the technical decision-making process. A Synthesized Model of Technical Decision-making in Product Development (Figure 37) was developed by integrating the unified model with the decision context and the outputs of the qualitative research. The synthesized model is the basis for the subsequent quantitative research.

The quantitative research builds on the results of qualitative analysis by expanding the synthesized model with numerical analysis. The biases discovered during the qualitative research were part of the synthesized model analysis. Survey research was done on a population sample to test the existence of the biases in technical decision-making process. Based on the results of the survey, statistical analysis was used to evaluate the significance of the biases in the model.

3.2.1 Population

The population of the study was project team members and stakeholders who take part in the decision-making process in product development (Table 2). The responsibilities of the commercial stakeholders, represented by project and product managers, are to ensure the fulfillment of business needs and adherence to financial constraints. Technical team members, such as system engineers and subject matter experts, would propose solutions that fulfill the project requirements. Each stage in the product development process must go through decision gates or milestones to ensure the project meets the business and technical requirements and that the risk of proceeding to the next stage is under control (Haskins et al., 2006). The gate approval is based on the agreement of the decision-makers, i.e., suitably qualified experts and involved stakeholders.

Table 2: Research population

Personnel Management	Project Management	Technical
Director	Project manager	System engineer
Department manager	Program manager	Development engineer
Group leader	Product manager	Research engineer
		Subject matter expert

Since it was beyond the means and time frame of this study to gather data from the whole population, sampling was required. There are two types of sampling methods: nonprobability and probability sampling, which can be further divided into sampling sub-types (Babbie, 2010). Probability sampling is done through random selection of participants, while participants in non-probability sampling are subjectively selected. Since qualitative and quantitative analysis require different sampling strategies, the sampling strategies will be discussed in their respective sections.

3.2.2 Qualitative Research

Qualitative research is a scientific method that explores individual and group behaviors to understand social and human problems by gathering non-numerical data through inquisition and observation (Babbie, 2010; Creswell, 2009). Qualitative methods are central to many fields, especially social science, due to their orientation towards behavioral reactions. Behavioral reaction maintains that human actions and body language are the result of their interpretation of the social world (Given, 2008). Capturing this symbolic interaction is crucial in understanding the human decision-making process. Therefore, approaching decision-making topics through qualitative research is imperative to grasp the nuances of human behavior.

The author's personal experience in organizational decision-making topics, especially within engineering organizations, can be both advantageous and disadvantageous to the thesis analysis. On one hand, the experience provides the author with the contextual knowledge to explore decision-making in depth, which will increase the probability of meaningful analysis. On the other hand, it causes the author to analyze the problems through a biased lens which then narrows the scope of the research and may mislead the research direction based on the author's predisposed understanding of the topic. Thus, in order to be an impartial researcher, it is important to begin the research by exploring the landscape of organizational decision-making. Therefore, the objectives of this qualitative research, which were derived from the research questions [RQ], are to:

- Gather information on participants' understanding of their organization- and industry-prescribed product development processes. [RQ1.1]
- Understand the participants' approaches to making technical decisions in their daily work. [RQ1.2]
- Observe differences between the participants' decision-making process and their organization's prescribed process. [RQ1.2]
- Solicit participants' biases in making technical decisions. [RQ1.3]
- Verify the unified model of rational and behavioral technical decision-making (Figure 23) in the product development process.

3.2.2.1 Sampling Method: Non-Probability Purposive Sampling

Small sample sizes are typical in qualitative research since it frequently examines a small number of subjects in great detail (Marshall, 1996). To enable a thorough examination of the landscape of decision-making processes in engineering firms, a small number of participants must be carefully chosen size to reflect the population. In light of this, non-probability purposive sampling is used to acquire qualitative data. Non-probability purposive sampling is a sampling method that requires a strategic sample selection based on the population that is aligned with the objectives of the research (Babbie, 2010; Given, 2008). The sample was selected based on the participant demographics: years of experience, type of industry, and job position.

Based on the literature, there is no consensus on the minimum required size or the method to calculate sample size for qualitative research (Sandelowski, 1995). Data saturation and pragmatic considerations have been used as the guiding principles in determining the sample size (Francis et al., 2009; Morse, 1995; Vasileiou, Barnett, Thorpe, & Young, 2018). Data saturation in purposive sampling can be achieved by "selecting only individuals who meet a specific criterion defined on the basis of their role in the implementation process" and expanding and narrowing the field of view during data collection (Palinkas et al., 2015, p.7). Data was collected until no new information emerged, or, to put it another way, until the data had reached its saturation point. For this research, a saturation point was reached with 15 participants.

3.2.2.2 Research Instrument: Interview

This thesis employed interviews as the main research instrument to collect qualitative data. The literature review of data lacks the analytical feedback loop of an interview. Since an interview is a dynamic process, an iterative in-depth inquiry into specific topics is possible. The data collected can also be interpreted objectively because the data source can provide immediate clarification of meanings. Therefore, the exploration of organizational decision-making processes through the lens of the decision-makers is particularly effective via interviews.

Qualitative interviews are generally conducted using semi-structured and open-ended questions with the intention of eliciting participants' views on a particular issue or phenomenon (Creswell & Plano Clark, 2007). The interviewer would have a plan of inquiry on the specific topics to be covered, but not a rigid set of mandatory questions to be asked (Babbie, 2010). The important aspect of a qualitative interview is to ensure openness and flexibility of the discussion. The questions asked at the outset of the interview should prompt responses that shape the direction of subsequent questions, which allows the interviewer to probe deeper into the earlier responses (Babbie, 2010). However, it is important during the interview to steer the discussion from going off-tangent from its intended path. This can be done by limiting the number of main topics to ensure a smooth and logical transition from one topic to another (Rubin & Rubin, 2011). This research adhered to the above protocols to ensure quality responses from participants.

Data collection through interviews, surveys, or observations is considered intrusive research (Duignan, 2016). Since the subjects are aware that their responses are being recorded, the interview process may influence participant behavior and may cause a discrepancy between their verbal responses and their actual sentiments. The intrusive effects can be reduced by employing audio recording to gather data, rather than writing notes, which allows the interviewer to make more eye contact with participants (Given, 2008). So, the interviews were audio recorded and then transcribed before the data could be used for analysis. However, there was also a possibility that interviewees were less open in their responses if they knew their exact words were being recorded using audio or video.

3.2.2.2.1 Research Ethics

The interviews were also conducted to ensure the anonymity of the participants and the confidentiality of the collected data. Anonymity in qualitative research is not only a standard practice but also an ethical issue to be considered (Given, 2008). Protecting participant identity in any ensuing reports or publications helps participants to freely discuss their views on subject matters without any fear of repercussion. Participant personal information was not recorded before, during, or after the interview. Data collected from participants were treated with the utmost confidentiality. Audio recordings and interview transcriptions could not be traced to any specific participant and the data will be expunged 6 months after the submission of this thesis. The above data collection protocols were strictly adhered to demonstrate the confidentiality of participant responses. According to UCL Research Ethics Committee (REC), the qualitative research did not require ethical approval through the UCL REC as it fell under exemption 4: “Research involving the use of non-sensitive, completely anonymous educational tests, survey and interview procedures when the participants are not defined as "vulnerable", and participation will not induce undue psychological stress or anxiety."

3.2.2.2.2 Instrument Development

Qualitative interviews were used to gather data from predefined population samples to fulfill the qualitative research actions. Interview questions were devised to better understand the decision-making processes of the participants' organizations as well as their personal decision-making process, and to verify the unified model of technical decision-making (Figure 23) as the conceptual framework.

Eight questions were prepared for the interview. The interview structure was flexible to adapt to the flow of the questioning, which depended on the dynamics of the interview. Therefore, the specific order of questioning was not emphasized, and related questions were asked depending on the responses of the participants. Additional questions were asked to clarify participants' responses. Further probing was also conducted to uncover new or more in-depth information. The questions were open-ended in nature to allow participants the liberty to elaborate and dwell on their responses. It is important to supplement the questions with sufficient context to provide clarity to the participants (Given, 2008). So, the researcher furnished participants with adequate information to set the scenario.

The questions were divided into two sections: preliminary and in-depth. Preliminary questions aimed at understanding participant's roles in their organization and their organizational decision-making processes. In-depth questions probed deeper into participants' thoughts by inquiring about their approaches to technical decision-making and identifying any cognitive biases that occur during the decision-making process.

Preliminary questions:

- *What kind of technical decisions do you make on a daily basis?*

The first question sets the tone for the rest of the interview. Participants were asked to provide a few examples of technical decisions they made on a daily basis. Depending on their answer, the interview structure was adapted accordingly, and the ensuing questions would be paraphrased to provide context based on their job functions.

- *Does your organization prescribe technical decision-making methodologies or guidelines?*
- *How do you, personally, make technical decisions?*

The next questions delve into the specifics of decision-making processes according to the participants' perspectives. The participants were questioned about whether their organization mandated or recommended a structured approach to technical decision-making, and whether they provided supporting processes on the matter. Additionally, participants' views on the value and efficacy of these processes were elicited.

The participants were also asked to describe their decision-making preferences. Since technical processes in industry are dominated by rational analysis and rule-following behaviors, as discussed in Chapter 2.5.1, deviations between the participant's decision-making process and the one specified by their organization were documented. Signs of the propensity of cognitive and social biases were investigated further during the in-depth questioning.

In-depth Questions:

- *How do you decide if a decision has to be made using an analytical process or personal judgment?*

In-depth questions were asked next to probe the participants' bias tendencies in decision-making. The first in-depth question examined the participants' reasoning for choosing between an analytical approach or trusting their instincts to make technical decisions. The selection criteria and the decision scenarios were recorded. The next questions were,

- *If an analytical process is applied to help decision-making, how do you choose between the alternatives?*
- *How do you evaluate the information that is provided to make specific technical decisions?*
- *If a decision has been made and new information is provided afterward, what do you do?*

These questions attempted to verify the existence of information processing, alternative selection, and decision revision group biases in the technical decision-making process as proposed in the unified model. These open-ended questions were structured in a way that participants could freely express themselves without feeling compelled to conform to socially acceptable answers. This is especially important to ensure that they were not aware of their own biases and thus would respond to the questions differently. The nuances in their responses were scrutinized to detect hints of biases in their decision-making processes. When biases were detected, additional questions would be asked to understand the reasoning behind their responses.

3.2.2.2.3 Data Gathering Methods

The interviews, as a data gathering method, were conducted in two ways: through personal and online interviews. In place of the personal interview, a 1-hour appointment was agreed upon with the participant at a predetermined time, date, and platform. A Skype or Microsoft Teams meeting invitation was sent to participants to set up the online interview appointment.

During the interview, participants were given a participant information sheet that explained the purpose of the study, the procedures of the interview, and participants' right to data privacy and anonymity of their participation (Appendix A). The interviewer had a set of interview guides (Appendix B), which contained interview objectives, protocols, and questions. Audio recording was used during the interviews to record the conversation with the consent of the participants. At no point during the interview were notes taken to maintain eye contact with the participants and to ensure that their responses were carefully listened to identify any underlying messages and follow-up questions that may be appropriate.

Following the interview, the audio recordings were transcribed using an automated transcription service. The transcriptions were then checked for grammatical errors and reviewed for sentence fluency. Both audio recordings and transcripts contained no personal information to ensure participant anonymity and data privacy. The final transcripts were then ready to be analyzed.

Following the interview, the audio recordings were transcribed using an automated transcription service. The transcriptions were then checked for grammatical errors and reviewed for sentence fluency. Both audio recordings and transcripts contain no personal information to ensure participant anonymity and data privacy. The final transcripts were then ready to be analyzed.

3.2.2.3 Data Analysis: Content Analysis

Content analysis is a qualitative research method that systematically analyzes the message characteristics of the intended content (Neuendorf, 2011). The analysis is widely used to analyze data from records, documents, interview responses, open-ended questionnaires, and other media (Babbie, 2010; Brough, 2018; Given, 2008). Data from the interview were analyzed using content analysis. There are three main steps of content analysis: definition of condensed meaning unit, classification process through coding, and identification of themes and patterns (Elo & Kyngäs, 2008; Hsieh & Shannon, 2005).

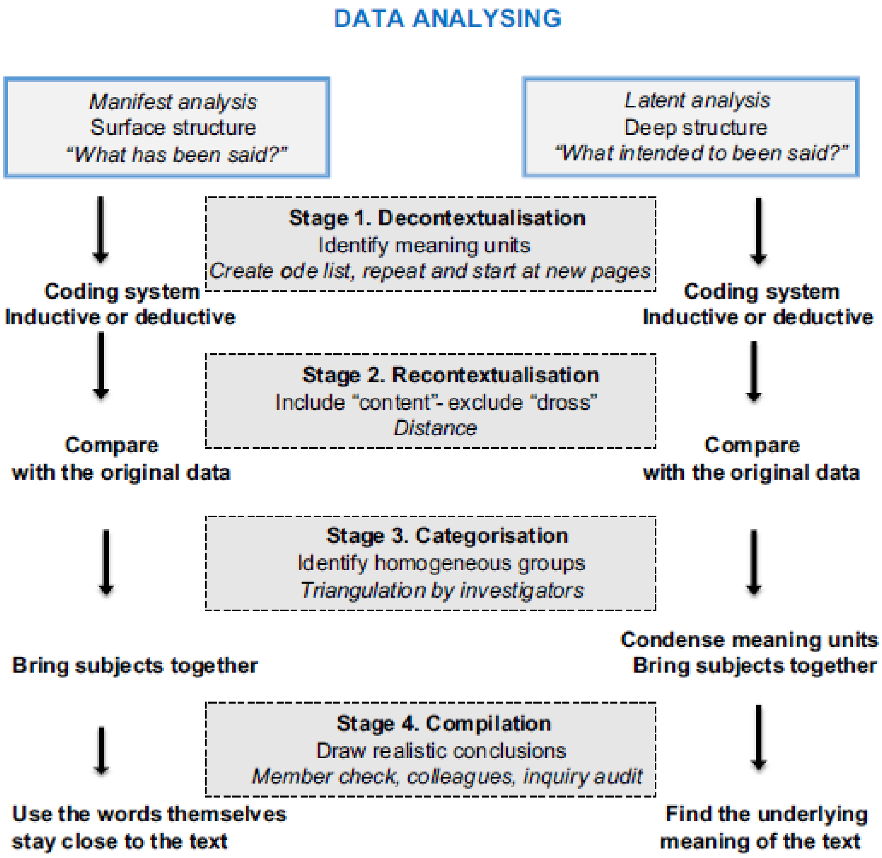

Figure 26: Content analysis process steps (Bengtsson, 2016)

Condensed meaning unit is the basic unit of text, where the content can be coded, categorized, and analyzed. The unit can be as broad as a whole book or as narrow as a paragraph or even a word in the documents (Babbie, 2010). Therefore, it is important to carefully choose the meaning unit, as it could render the analysis unmanageable or fragmented due to its inappropriate size (Elo et al., 2014). The interview is divided into 8 sections based on the prepared questions. The participants' responses were analyzed in each section and broken down into multiple chunks of manageable units that became the foundation of subsequent analysis.

Coding is the central theme in content analysis. It transforms raw data into a standardized form using a classification technique, to be quantified and analyzed (Babbie, 2010; Given, 2008). There are two types of content specified in content analysis: manifest and latent content. Manifest content is the surface content that is directly interpretable by the readers; latent content, on the other hand, is the underlying meaning of a text (Babbie, 2010). Different content types require different data analysis strategies, as shown in Figure 26. In manifest analysis, the codes are analyzed by utilizing the words found in the documents or by staying as near to the words as possible. Qualitative interviews yield latent content. Therefore, the author has to interpret the underlying meaning of the interview transcripts (Bengtsson, 2016) and derive codes with reference to the objectives of this analysis.

Developing themes is the process of summarizing the codes and placing them into categories or themes (Erlingsson & Brysiewicz, 2017). Themes of latent content are higher-level abstractions of coded data, whereas in manifest content, the themes express the data at an interpretative level.

make decisions in the right way. Or at least, to prepare the decisions in a concerted, let's say, completed holistic way and you need to decide each and every.. you need to select the right method for each decision	**Condensed Meaning Units**
Q: Right. So now, you see that there are some methodologies or guidelines. Can you give examples, maybe one or two or three examples?	
A: One example is for a technical change, either in planning production or in development. We definitely have to go through a Change Control Board, so we have to make a certain set of documentation available to a group of people that reviews the change. The set of documents usually include a document called	Technical change, either production or development issues, is made within a team through change control board

Example 1: Condensed Meaning Unit

Condensed meaning units (Example 1) derived from all interviews were collected in one location to be coded and classified (Example 2). The meaning units were separated based on their related questions to provide context for the responses. Then, for each condensed meaning unit, a code or set of keywords was assigned. After all interviews had been transcribed, analyzed, and coded, the codes were reviewed for consistency, and codes with similar meanings were combined to reduce overall code variation.

Questions	Part.	Condensed Meaning Unit	Codes	Theme
3. How do you, personally, make technical decisions?	A	Try to understand factors to make decisions, through gathering feedback from many people	Data gathering from experts	6
	B	Full DMP method is not followed	analytical process is not used fully	4
	C	Personal preference is using rational analysis, by systematically understanding the problem and use DRBFM	analytical process is preferred	4
	C	Engage the team to make decision	group decision making	1
	D	Any changes must go through impact analysis to check if the decision will impact technically or commercially	analytical process is preferred	4
	E	Group decision-making. Teams give inputs, he makes decision	group decision making	1
	F	Personal DMP is using analytical approach, decision matrix.	analytical process is preferred	4
	G	Checklist is the main source of DMP, but personal experience, based on intuition, is also used.	DM procedures are not always followed	11
	H	Systematically ruling out options based on personal judgement. If the leftover options are unclear to choose, cognitive trade-off table is being used.	Analytical + personal judgement: cognitive trade-off	4
	H	Trade-off criterias are based on technical, financial and time aspects: If no best solution can be found, the next best one is chosen	cognitive trade-off is based on weighted criterias	10
	I	Technical decisions, with suppliers, are normally made without involvement of management if agreement can be reached	management involvement for critical decision	13

Example 2: Coding

Finally, the codes were analyzed to find the overarching themes. They were compiled, combined, and generalized to create higher-level forms of abstraction (Example 3). The full content analysis can be found in Appendix C.

1	Technical decision-making is an overwhelmingly group effort. Group is involved to gather information, make decision and reevaluate previously made decision
2	Not all organizations prescribe decision-making guidelines; when they do, the guidelines are normally not properly documented, and the level of detail is inconsistent

Example 3: Themes

3.2.3 Quantitative Research

Quantitative research is a numerical approach to empirical analysis, that is in contrast to qualitative type of research (Given, 2008). It focuses on systematic measurement of variables, understanding the causal and correlational relationship between the variables, and testing or generating hypotheses. It is a valuable tool to answer some of the research questions posed in this thesis.

As discussed earlier, this thesis employed a mixed-method strategy, specifically the *sequential exploratory strategy* (see Section 3.1). The layered approach of the strategy has the quantitative research built on the results of qualitative analysis by expanding the synthesized model (Figure 37) with numerical analysis, where the data were gathered through a survey and analyzed using statistical analysis tools. The qualitative analysis earlier yielded key points that were used in the quantitative research.

Based on the sequential exploratory strategy, the quantitative research component of this thesis builds on qualitative research by analyzing the impact of biases on the objectivity of technical decision-making through an empirical study. The study employed a survey to gather data that was then analyzed using Exploratory Data Analysis. The objectives of this quantitative research, which were based on the research questions [RQ], are:

- To test the significance level of the identified biases in the technical decision-making process [RQ1.4]
- To examine relationships between the identified biases and decision analysis in the technical decision-making process [RQ1.4]

3.2.3.1 Sampling Method: Probability Stratification Sampling

In quantitative research, samples are selected from the population to provide its statistical characteristics. Some of the statistical outputs are the mean, variance, and correlation of variables of the population (Singh, 2007). In some cases, a probability sampling error can be introduced into the analysis due to an ineffective population sampling strategy and this causes the sample to be unrepresentative of its population. Probability sampling error depends on three factors: sample size, population diversity, and confidence level (Babbie, 2010). One of the techniques to reduce the sampling error is stratifying or dividing the population into groups that are relevant to the objective of the overall research. This is to reduce the probability of any one of the groups being left out and becoming underrepresented in the sample (Given, 2008). This technique is called probability stratified sampling.

In this study, the population was stratified into two levels, industry and organization roles and positions. The industries chosen were all focused on safety-critical systems, such as space, automotive, and medical devices, while the organizational roles and positions were project management, personnel management, and engineering. This selection ensures that various roles and industries are represented in the technical decision-making process.

3.2.3.2 Definition of Variables

In quantitative research, a variable is a vital concept. A variable is a measurable attribute of an individual that varies among the samples under study (Creswell & Poth, 2007). There are two main types of variables, independent and dependent, in which “an experiment examines the effect of an independent variable on a dependent variable” (Babbie, 2010, p. 232). Demographic characteristics of the population can have varying effects on the biases and risk appetite level during the technical decision-making process. The research variables were as follows:

Independent variables: years of experience, position, industry

Dependent variables: information processing bias cluster [individual bias: confirmation bias, ingroup bias], alternative selection bias cluster [subset: illusion of validity bias], decision revision bias cluster [subset: escalation of commitment, groupthink], risk appetite

Each bias cluster comprises one or two individual biases where the quantitative research examined both the bias cluster and the individual biases. Since this thesis hypothesizes the existence of multiple bias clusters in relation to decision analysis, the focus was on bias cluster analysis. Based on qualitative research analysis, risk plays a huge role in the technical decision-making process. Therefore, the quantitative research also looks into the effect of risk appetite of decision-makers in the technical decision-making process.

3.2.3.3 Research Instrument: Survey

A survey is a systematic research method to gather data from individuals, organizations, or other entities through questionnaires, focus groups, or observations (Given, 2008). Data analyzed from the survey can be used to test the significance of the identified biases and examine the relationships between variables. Survey design can be generally described using four aspects: the population and sample, method of survey, instrument design, and method of delivery (Creswell, 2009; Gorard, 2003).

In asking survey questions, open-ended and closed-ended options are available depending on the research actions. Close-ended questions can be further grouped into two types of questions: dichotomous and multiple-response. Dichotomous questions have two possible answers, such as true/false or agree/disagree, while multiple-response questions have three or more (Gorard, 2003). In many cases, participants generally respond more thoughtfully to open-ended questions, but ones that are closed-ended have higher consistency of replies and are easier to comprehend and analyze (Babbie, 2010). In this thesis, open-ended questions were already used in the interviews to explore the landscape of technical decision-making. Closed-ended multiple-response questions were utilized where respondents were asked to select an answer from a predetermined list.

3.2.3.3.1 Research Ethics

The survey, employed as a data gathering method, was conducted using two approaches: an online questionnaire (web-based survey tool) and an offline questionnaire (electronic copy of the questionnaire). Participants' personal information was not recorded at any stage—before, during, or after the survey. Data collected from participants were treated with the utmost confidentiality. Survey responses could not be traced back to any specific participant, and the data will be expunged six months after the submission of this thesis. These data collection protocols were strictly followed to ensure the confidentiality of participant responses. According to UCL Research Ethics Committee (REC), the quantitative research also did not require ethical approval through the UCL REC as it fell under exemption 4: "Research involving the use of non-sensitive, completely anonymous educational tests, survey and interview procedures when the participants are not defined as "vulnerable", and participation will not induce undue psychological stress or anxiety."

3.2.3.3.2 Instrument Development

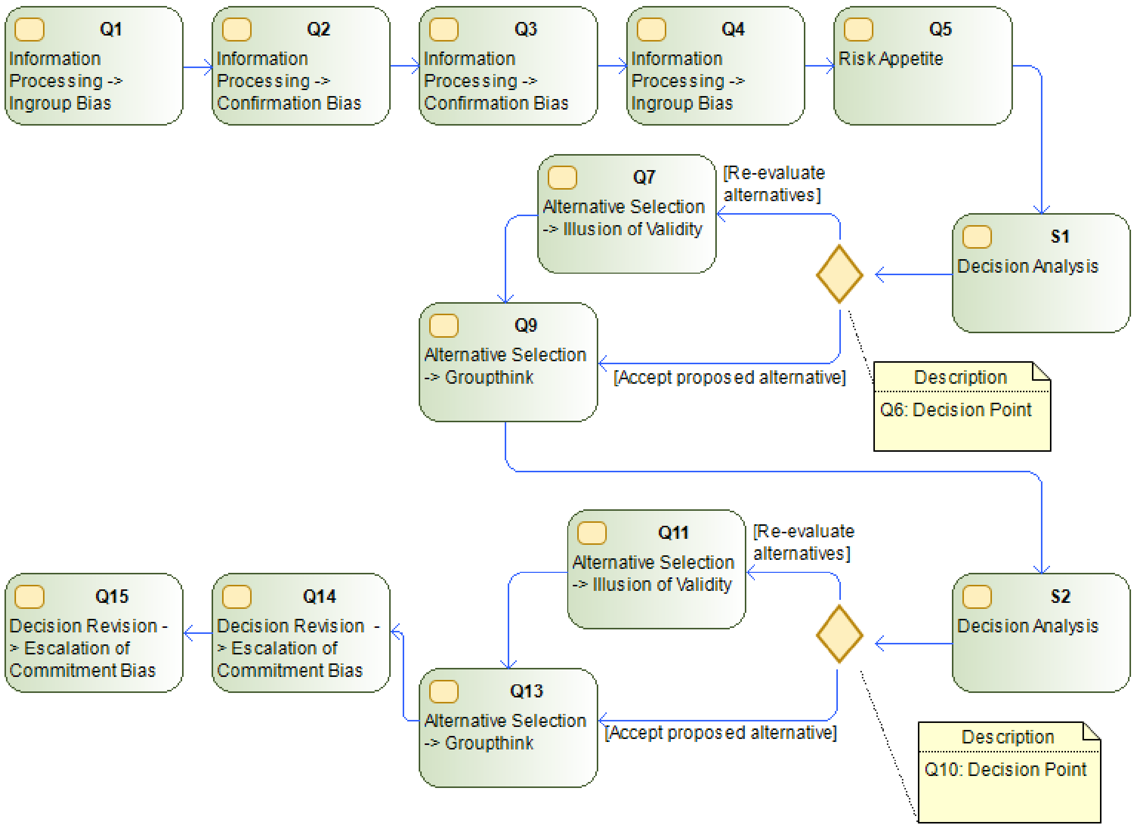

Figure 27: Questionnaire Flow

The questionnaires were developed to measure the bias inclination of participants during the technical decision-making process. In the scenario-based multiple-response questionnaire, participants were presented with a scenario that simulates a product development process in the industry. The scenario depicts a set of real-life decision-making situations that test the biases and risk appetites of the participants subtly. The questions were created in such a way that participants would not be aware of their own biases, while the scenarios were developed with examples and processes that were familiar to the participants. The questionnaire had four questions on demography: years of experience, role, industry, and organization, followed by the main questions related to biases and risk appetite. Figure 27 shows the flow of the questions. The full questionnaire can be found in Appendix E.

The questionnaire structure is mostly linear except for two branching questions (S1 and S2) after Q5 and Q9 respectively. The questionnaire is split into three parts: design development, concept selection, and design verification. In total, 15 main questions were linked to each other to form an overarching scenario of a product development process.

The first part of the questionnaire, Q1 to Q5, is about the design development phase where the participants were required to make technical decisions involving audit reports, supplier discussions, and design proposals. The first four questions test information processing biases, focusing on *ingroup bias* and *confirmation bias*, while the fifth question evaluates the participant’s risk appetite.

The second part was on concept selection. The participants were presented with two scenarios on the results of two decision analyses (S1 and S2). In Q6 and Q10, participants were given the choice to make the final decision for the two scenarios. At this point, the questionnaire would branch into different questions depending on their decisions during the concept selections. They would either be directed to Q7 (for S1) and Q11 (for S2) to test their cognitive bias inclination (i.e.: *illusion of validity*), or to Q9 (for S1) and Q13 (for S2) to assess their social bias tendency (i.e.: *groupthink*).

The last part of the questionnaire sets the scenarios for the final stage of product development: design verification. The participants were provided with another set of information that is critical to the success of a project, which made them reconsider their previously made decisions. Their *escalation of commitment bias* was tested, at Q14 and Q15, to understand if rationality would prevail or collapse under these stressful situations. In summary, each of the 15 scenario-based questions gauges the participants' bias tendencies and their risk appetite.

In each scenario-based question, participants were presented with a situation that simulated a product development process in their industry and were asked to determine the next course of action. As each scenario is designed to test a specific bias, there is no right or wrong answer. The participants would have to rely on their knowledge, experience, and decision-making inclination. For example, question 4, see the example below, tests the participant's ingroup bias. The participants were presented with a dilemma of whether or not to accept a supplier's proposal as is or to trust the team's feedback to challenge the proposal. In some questions, the participants would also have access to additional information when needed. Rational decision-makers strive for completeness of information; their response to the additional information sheds some insights into their decision-making process.

> *Supplier B proposes a design that uses highly reliable components to improve system fault tolerance and implements a fail-operational mechanism when failure occurs. This combination of safety mechanisms ensures lower risk probability and hazard consequences are under control. Supplier B promises that the control system development can be completed within 5 months. Upon discussion with your team, they believe that the timeline is ambitious and thus do not agree with the supplier's assessment. They argue that the design proposed by the supplier requires a great deal of development effort due to its complexity. Furthermore, many suppliers in previous projects had overpromised but under-delivered in terms of development time. Your team proposes to add a 2-week buffer to the supplier's development time.*
>
> *Do you accept your team's analysis regarding the feasibility of Supplier B's timeline?*

Example 4: Question 4's Scenario

All questions have responses, and each answer corresponds to varying degrees of bias inclination. The participants would not rate their answer by selecting a response using an attitudinal rating scale, for example: strongly agree to strongly disagree or -2 to +2. The attitudinal rating scale measures attitudes and opinions, it can be affected by participants' moods which can vary depending on many factors. Therefore, the participant's answer to the same question may change over time (Noh, 2011). Furthermore, the attitudinal rating scale is arbitrary because "it is not known where a given score locates an individual on the underlying psychological dimension" (Blanton & Jaccard, 2006, pg. 28). It cannot be objectively inferred that Participant A's rating of +2 is equivalent to Participant B's rating of +2 because both participants may have different scale of psychological dimensions.

As explained in the literature review, boundedly-rational humans lack a stable system of preference and thus their preferences can be volatile. To address this limitation, participants did not select an option using the conventional rating scale. Instead, they chose a response that had been assigned a specific, yet undisclosed, bias strength. Each response provided a potential solution to the decision scenario, with the bias strength of each response being predetermined by the author. Although the participants' biases were subjectively assessed, using the researcher's bias evaluation as a common reference point allowed for a more objective-oriented analysis.

A *strong* bias indicates that the participant clearly exhibits the bias under examination. In contrast, a *weak* bias suggests a minimal presence of bias, albeit not its complete absence. A *somewhat strong* bias signifies that the participant displays the bias in a noticeable yet moderated manner, suggesting that some level of objectivity is considered in their otherwise bias-influenced decision-making process. Conversely, when a participant is assessed as showing *somewhat weak* bias, it suggests a tendency towards impartiality, though bias is still present. In such cases, the participant is predominantly objective, yet their bias may still impact their cognitive reasoning. The explanation of the score of bias strength is as follows:

Bias strength	Definition
Strong	Participant clearly demonstrates bias
Somewhat strong	Participant demonstrates noticeable bias with mitigating factors
Somewhat weak	Participant demonstrates subtle bias, with a lean toward impartiality.
Weak	Participant minimally demonstrates bias

Table 3: Bias strength definitions

In the case of Question 4 (Example 5), if participants chose option A, this indicates a strong ingroup bias, reflecting a preference for team decision. Conversely, selecting option D suggests a weak ingroup bias, as it demonstrates openness to a supplier's proposal over team consensus. Option B reveals a somewhat strong ingroup bias, demonstrated by a cautious acceptance of their group's proposal by which participants reviewed the supplier's proposal with the group. Lastly, opting for Answer C implies a somewhat weak ingroup bias, as it indicates neither rejection of the group's proposal nor full endorsement, but a preference for impartiality by requiring justification from the supplier.

However, in some cases, participants may be compelled to make a choice that they would not have made otherwise due to a lack of available options. This non-exhaustive response set may introduce bias of its own (Gorard, 2003). Therefore, to address this, participants were given an option where they could write their own responses as shown in Example 5. Since each question only tests a specific bias, the responses only reflect the participants' susceptibility to that particular bias. Other biases might also be at work when the participants chose a specific answer, and this situation cannot be neglected.

Answer	**Bias strength**
A. Request Supplier B to add 2 weeks buffer to their timeline	Strong Ingroup Bias
B. Review the supplier's work breakdown structure and development schedule with your team	Somewhat strong Ingroup Bias
C. Require Supplier B to justify their proposal	Somewhat weak Ingroup Bias
D. Accept the supplier's proposed development time	Weak Ingroup Bias
E. Other (please comment):	

Example 5: Question 4's Answers

Scales of measurement need to be clearly defined during research instrument development in order to ensure the gathered data can be analyzed to achieve the research actions. The questionnaire employs nominal, ordinal, and interval scales for different sets of questions, depending on the type of analysis required. Demographic questions are independent variables using a nominal scale, for *position* and *industry*, and an ordinal scale for *work experience*. Participant demographics will be used to analyze the dependent variables by providing multiple viewpoints of the same data set. The scenario-based questions will require A different approach to measurement scales.

The scenario-based questions use an attitudinal scale in order to bring objectivity into subjective concepts, as it quantifies abstract behavior and attitudes (Singh, 2007). The majority of the questions use unipolar 4-point Likert scales. The Likert scale was developed to measure the attitudinal scale by allowing mathematical operation on the summated responses (Likert, 1932). The unipolar 4-point scale is an asymmetrical scale with four interval points as follows: strong, somewhat strong, somewhat weak, and weak, with no neutral point. The asymmetricity allows for the measurement of the presence of a particular bias. Meanwhile, a neutral scale is not used because the total absence of a specific bias cannot be objectively guaranteed. Likert scale data can be analyzed using an interval measurement scale by calculating composite (summated or mean) scores of similar Likert-type questions (Clason & Dormody, 1994; Likert, 1932). There is no consensus on the minimum number of questions required; it can be as few as two or three, but four or more is generally recommended to reduce measurement error (Albaum, 1997; Diamantopoulos et al., 2012; Hinkin, 1995). On the other hand, analyzing individual, not composite, Likert-type questions shall be done using an ordinal measurement scale (Clason & Dormody, 1994). Therefore, the measurement of scales to be used in the quantitative research can be summarized as follows:

- Nominal: Demographics
- Ordinal: Demographics, Risk appetite, Individual bias
- Interval: Overall bias, Bias cluster, Bias type, Bias in risky situation

Reliability and validity of the questionnaire need to be established in order to ensure consistency of measurement and that it truly measures what it was designed to measure (Given, 2008). This research uses the *multiple forms* technique to increase its reliability by testing the same bias twice in different forms (Singh, 2007). Each bias would be tested in two separate questions, using different sets of mini-scenarios, at different points along the questionnaire. The questionnaire was also subjected to *content validity*. Content validity ensures that the measure accurately reflects the content of the concept under consideration. This was accomplished by asking two subject matter experts whether the survey questionnaire accurately measured the idea intended to be measured (Singh, 2007). The two domain experts in systems engineering and social science possessed in-depth knowledge of organizational decision-making and engineering management. They reviewed the structure of the questionnaire and provided critical feedback on how the decision scenarios could be utilized to measure participants' biases. This includes the formulation of Table 3 and Table 4 and its subsequent transformation into Table 9. In addition, the questionnaire was pre-tested in a pilot study with a sample of two persons who fulfilled the target group demographics. Their responses to each question and feedback regarding the clarity, flow, and structure of the questionnaire were taken into consideration and the questionnaire was duly updated.

3.2.3.3.3 Data Gathering Method

A survey can be administered through face-to-face delivery, telephone calls, mail-based or online-based self-administration (Babbie, 2010; Gorard, 2003). For the study, the questionnaires were administered using the web-based survey tool, qpointsurvey.com, and survey invitations were distributed through emails and professional social networks (i.e.: LinkedIn). In cases where there were technical problems with the web-based survey tool, the respondents were sent a soft copy of the questionnaire. Both soft-copy and web-based survey outputs were compiled into one dataset to be analyzed together.

Respondents were selected based on the previously defined population demographics (see Section 3.2.1). Responses from respondents who did not fit into the demographics were discarded during data cleaning. Since the demographics of respondents were specific to a particular group, purpose sampling was done. To achieve a target of 90 respondents, the author requested contacts from his current and previous employments, particularly those in the medical device and automotive industries, to be the respondents. Other respondents with the same background were also approached directly via LinkedIn or through UCLse connections with the Mullard Space Science Laboratory and European Space Agency.

3.2.3.4 Data Preparation

Data preparation is an important step in statistical analysis to filter out noisy or incomplete data, improve the efficiency of data selection, and increase the quality of the final data (Zhang, Zhang, & Yang, 2003). This research utilized a two-stage approach in data preparation: data cleaning and data transformation as follows:

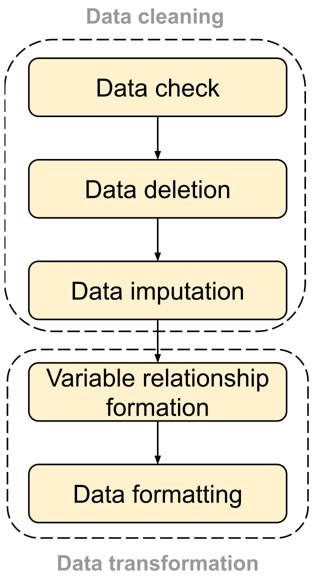

Figure 28: Data preparation process

The purpose of **data cleaning** is to eliminate obvious errors, such as missing values, skips, or inconsistent entries using cleaning techniques such as range checks, missing values, and data checks (Singh, 2007)**.** Range checks are applicable for continuous data such as height and weight, and the gathered data should be within a specified range. In the case of this research questionnaire, the respondents were given discrete options, so the range check was not necessary. For example, in the questionnaire, respondents were given 4 numerical discrete options (Figure 29**)** on work experience and they were required to pick one option.

Work experience:
☐0-3 years
☐4-7 years
☐8-12 years
☐13+ years

Figure 29: Non-continuous categorical variable

Missing values in questionnaire datasets are common, and these can be attributed to many factors such as systemic error in administrating questions or respondents declining to respond to questions (Singh, 2007). Checking the missing values is important because incomplete data may skew the results of the analysis.

Therefore, the missing data needs to be dealt with by either deleting or suggesting a new value in lieu of the data.

Data can be deleted systematically using *list-wise deletion* or *pair-wise deletion* techniques (Singh, 2007). In *list-wise deletion*, a case that has missing data will be deleted completely. This not only reduces the sample size available for statistical analysis but also may systematically remove a certain group of correspondents. (Hair, Sarstedt, Ringle, & Mena, 2012; Treiman, 2009)**.** Therefore, instead of dropping the whole case, *pair-wise deletion* preserves the available data by evaluating all cases in which the variables of interest are present and thus keeps the sample size constant. In this deletion method, the statistical analysis uses all available cases even when some of them may contain missing data. However, the analysis cannot include a case when it has a missing value of a particular variable, but it can still use the case when analyzing other variables with non-missing values. The disadvantages of this method is that the different variables may yield different sample sizes and thus, can bias the results (Hair, Hult, Ringle, & Sarstedt, 2016; Singh, 2007).

Missing data can also be imputed with new values. Imputation is the process of replacing missing values with estimated values using mathematical and statistical models (Marsh, 1998). There are multiple imputation techniques available, such as mean substitution, regression analysis, Maximum Likelihood Estimation (MLE), Multiple Imputation (MI), and Hotdeck method. MLE is the chosen technique in this research because of its superior method due to its accuracy over MI especially for small sample size and non-normal data, and its performance over regression analysis (Shin, Davison, & Long, 2016; Singh, 2007)**.**

Out of 131 questionnaires sent out to potential respondents, 89 respondents fully completed the questionnaire, 7 partially completed it and 35 of the responses were considered incomplete. The main reasons for the incompleteness were lack of time and failure of internet connection. Therefore, different missing data treatment strategies were used for the different levels of questionnaire completion, as follows:

- Complete: No missing data, no further action
- Partially complete: Data imputation using Maximum Likelihood Estimation
- Incomplete: Data deletion using List-wise Deletion

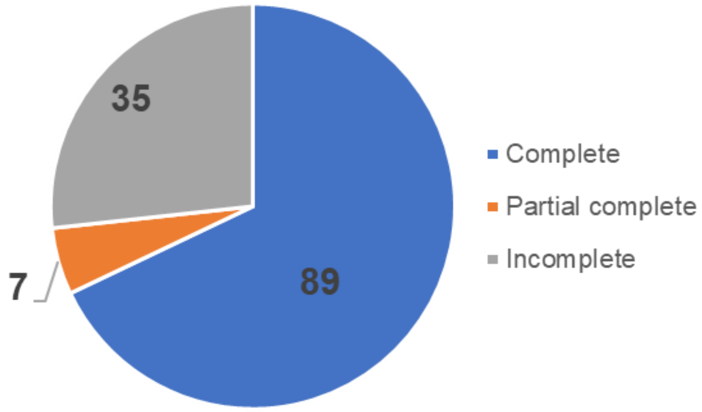

Figure 30: Questionnaire completion rate

Missing data can be classified as Missing Completely At Random (MCAR) when the missing variables are independent of the values of any other variables in the dataset (Treiman, 2009), which is the case for the collected data. So list-wise deletion, as the selected method for data deletion, is suitable for the missing data (van Buuren, 2012). Deleting 35 cases reduces the sample size significantly. However, the decision not to impute the data for the incomplete cases was to avoid conflating the data with artificial values that would reduce the value of the analysis. The next step in data cleaning was to impute the remaining partially completed data with new values.

Maximum Likelihood Estimation is a method that estimates unknown parameters of an observed statistical model, by finding parameter values that maximize likelihood to fit into the observed data (Treiman, 2009). Each case with missing data was grouped according to its relevant demographic group (i.e.: work experience and position) before the MLE process was executed. This was to ensure the estimated new value fitted the demographic distribution curve. Using one of the SPSS "missing variable analysis" features, Expectation Maximization, 7 cases with missing data were populated with statistically estimated new values. Once data cleaning was complete, the total usable cases were 96 and the data was transformed to fit the selected statistical tools requirements.

Data transformation establishes functional forms between variables and converts the data from the original format into the required format of the target application

(Fink, 2009; Miller, 2017), which was Python-based EDA. Since the target application accepts numerical values, raw data from the questionnaire must first be converted from textual data to a quantifiable form. As each response corresponds to a specific bias strength, the response is replaced with a numerical value as per the Likert scale (Table 4). If respondents provided their opinions by opting for Option E, the author would assess the answer, determine the bias strengths individually, and assign its corresponding numerical value.

Table 4: Data conversion

Responses	Bias strength	Numerical value
A. Predefined	Strong	4
B. Predefined	Somewhat strong	3
C. Predefined	Somewhat weak	2
D. Predefined	Weak	1
E. User input	To be determined	

The next step of data transformation is to establish functional forms between variables based on the selected statistical methods. With this in mind, a data structure (Figure 31) was created to establish the relationship between latent variables and measured variables from the questionnaire. Latent variables such as individual bias, bias cluster, bias type, and overall bias variables are direct and indirect composite scores of the measured variables from the questionnaire, as per Figure 31. On the other hand, demographic and risk averseness variables use the values directly from their corresponding measured variables.

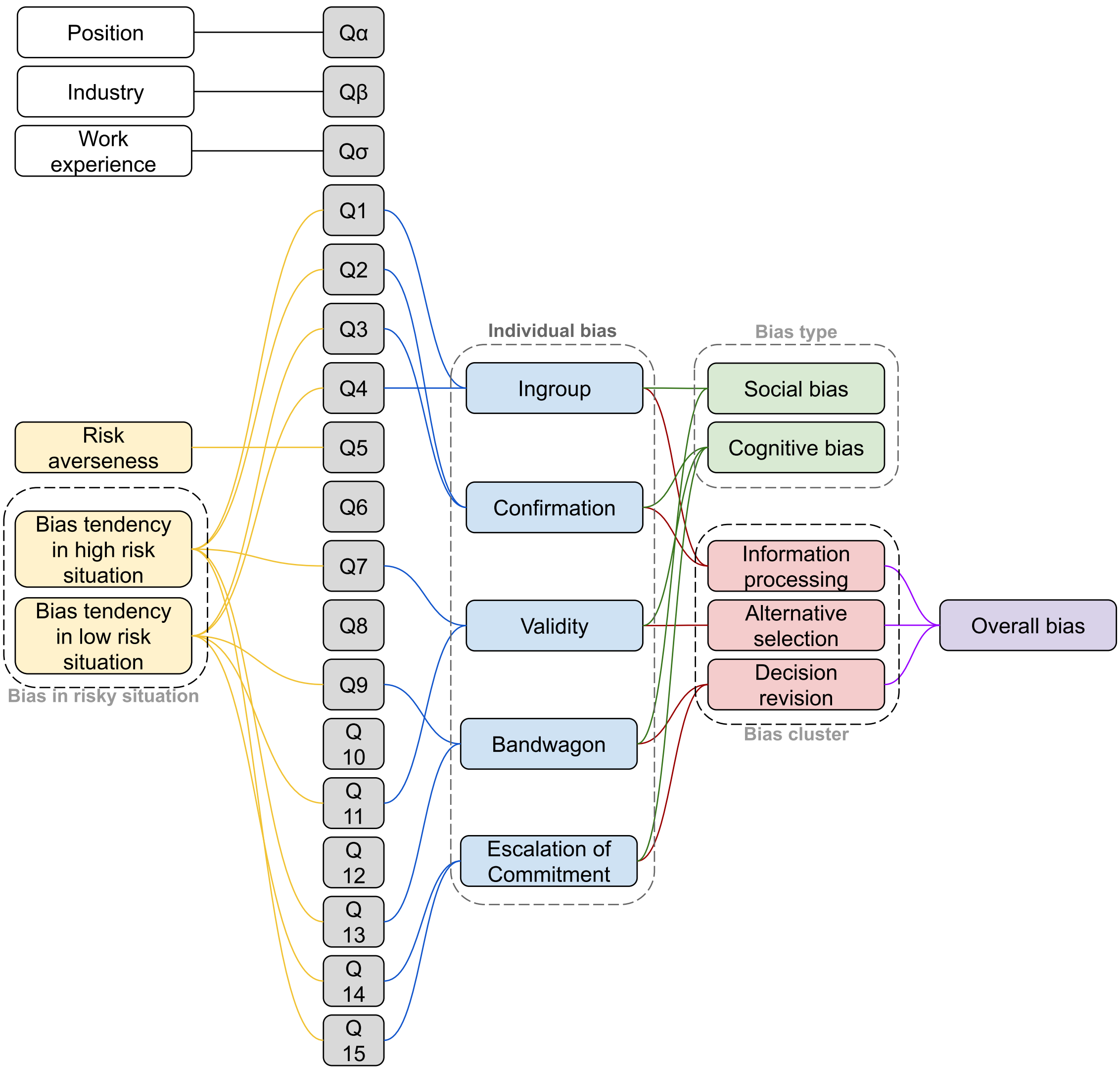

Figure 31: Questionnaire Variable Data Structure

3.2.3.5 Data Analysis: Exploratory Data Analysis

Exploratory Data Analysis (EDA), established by John Tukey in his seminal work in 1977, *explores* data for distribution and anomalies by visualizing the data through graphical representation and numerical means (Tukey, 1977). The goals of the analysis are not to confirm hypotheses but to understand the dataset, recognize patterns and potential relationships between variables, or formulate hypotheses (Fuentes, 2018). In research, graphical EDA uses various plots to explore the data in order to identify relationships or patterns between the variables. Understanding types of variables is crucial in selecting the best graphical EDA techniques and corresponding statistical tests.

Nominal, ordinal, and interval data require different statistical analyses. Participant demographics are independent variables and made up of nominal and ordinal data, while dependent variables are composite data of four or more similar Likert-type questions that can be treated as interval data (Figure 31). These data can be analyzed with univariate analysis using central tendency and dispersion analysis or multivariate analysis using regression analysis or factor analysis (Fornell, 1985; O'Leary, 2004). Four plot types were used to explore the data using graphical EDA: histogram, count plot, box plot, and scatter plot.

A histogram (Figure 32) consists of multiple bars that represent the frequency (or count) of a range of values. Histogram plots visualize the distribution type of the dataset, identifying whether it is normal, beta, exponential, or multi-modal. Understanding the distribution type of a dataset is important when selecting an appropriate statistical test. This plot is typically employed in univariate analysis; using it to compare two or more variables in a multivariate analysis can be problematic because overlapping multiple plots in the same graph can make interpreting the data challenging.

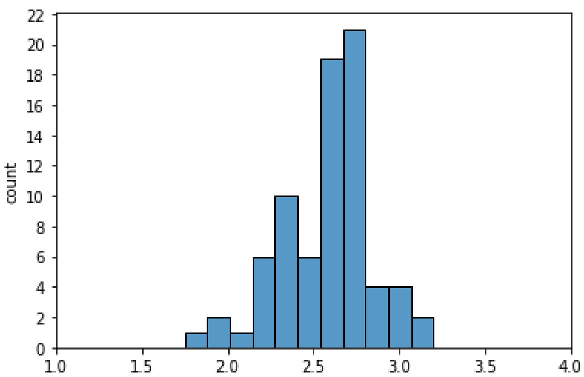

Figure 32: Histogram

A count plot (Figure 33) is similar to the histogram as it shows the frequency of observations in each bin. However, the count plot focuses on categorical variables, whereas the histogram with numerical variables. This plot can be used in univariate and multivariate analysis to compare different clusters across different variables.

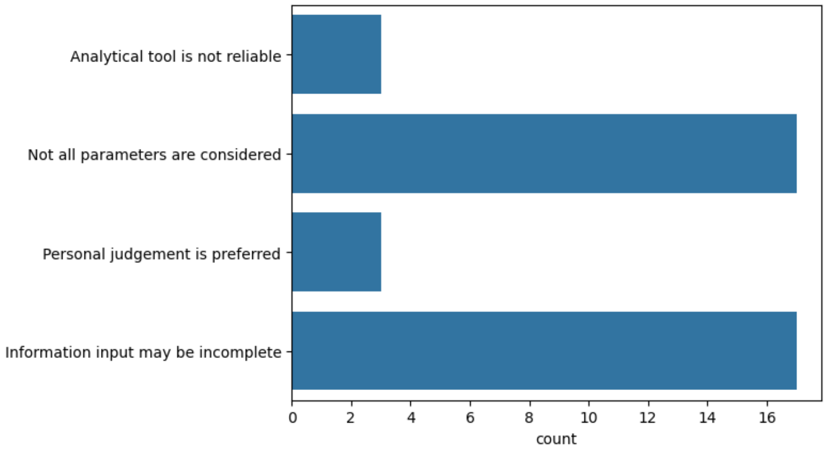

Figure 33: Count plot

A box plot (Figure 34) provides different perspectives of the same dataset. The box plot denotes the distribution of the data by specifying the maximum and minimum value and interquartile range at the 25th and 75th percentile. It also shows median information and potential unusual observations, or outliers, in the dataset. However, box plots can only show the skewness of a data distribution, but not the type of the distribution. In a multivariate data analysis, categorical and numerical variables can be easily compared using a box plot as the plots are shown side by side in the graph as opposed to the overlapping bars in a histogram.

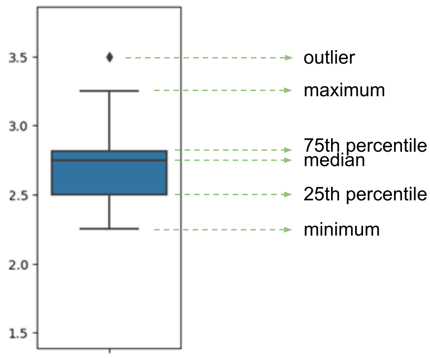

Figure 34: Box plot

A violin plot (Figure 35) is largely similar to the box plot in terms of data presentation. However, it better represents the data distribution by visualizing the probability density, which is calculated using kernel density estimation. Kernel Density Estimation (KDE) estimates data point distribution without making any assumptions about the underlying distribution.

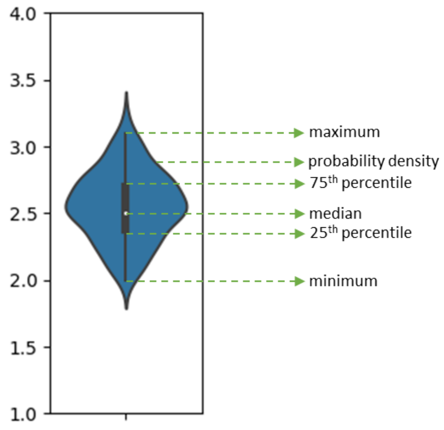

Figure 35: Violin plot

A scatter plot (Figure 36) uses dots to represent the values of two numerical variables. It is made up of two axes: a horizontal axis with the measured value of one variable and a vertical axis with the measurement value of the other. The purpose of a scatter plot is to show the relationship between two or more variables. Therefore, in multivariate data analysis, the plot can visually suggest various types of correlations between numerical variables. However, it cannot show the frequency of a specific value in the dataset.

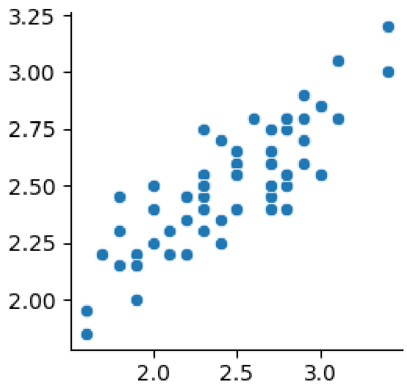

Figure 36: Scatter plot

So, graphical EDA can visually demonstrate relationships or patterns between the variables, but the interpretation of the graphs is subjected to human biases and errors. Therefore, to address this shortcoming, statistical analysis was used to determine objectively the significance of the results.

Statistical analysis can be divided into two types: association (correlation and regression) and comparison (Singh, 2007). The purpose of a correlation analysis is to understand the strength of the relationship between variables, while a regression analysis identifies cause and effect, or the strength of the relationship (Treiman, 2009). Comparison analysis, on the other hand, measures the difference of means or medians between variables (Singh, 2007). A hypothesis can be proven through the significance of the statistical analysis. The null hypothesis is rejected if the calculated p-value is less than the alpha value, which is conventionally accepted as 0.05 (Di Leo & Sardanelli, 2020). A value of $\alpha = 0.05$, also known as the significance level, "implies that the null hypothesis is rejected 5 % of the time when it is in fact true" (National Institute of Standards and Technology, n.d.), where a result is deemed statistically significant based on the collected samples if the p-value < 0.05.

In order to select the appropriate statistical tests for variables under investigation, the sample parameters, such as normality, variable type (continuous or categorical), number of samples, and dependency between the groups, should first be identified (Singh, 2007). Table 5 guides the selection of comparison statistical methods. Based on quantitative research actions and dataset characteristics, One-way ANOVA, Unpaired T-test, Wilcoxon Signed Rank, and Pearson Correlation tests were used to test the statistical significance of the dataset.

		Non-parametric Test	
Goal	*Parametric Test* *Gaussian Population*	*Rank, Score or Measurement*	*Binomial (Two Possible Outcomes)*
Compare one group to a hypothetical value	One-sample t test	Wilcoxon test	Chi-square or binomial test
Compare two unpaired groups	Unpaired t test	Mann-Whitney test	Fisher's test
Compare two paired groups	Paired t test	Wilcoxon test	McNemar's test
Compare three or more unmatched groups	One-way ANOVA	Kruskal-Wallis test	Chi-square test
Compare three or more matched groups	Repeated-measures ANOVA	Friedman test	Cochran Q

Table 5: Types of statistical tests (Singh, 2007)

The normality of the sample data distribution must first be determined as different distributions require a different set of tests. The Shapiro-Wilk Test for Normality determines the normality of a variable distribution, with the null hypothesis being that a dataset is normally distributed (Shapiro & Wilk, 1965). The test demonstrates normality either from the sample skewness, kurtosis, or both (Althouse, Ware, & Ferron, 1998). A sample is deemed to be not normally distributed if the null hypothesis is rejected, and thus requires non-parametric tests; Otherwise, parametric tests are required.

The Two-tailed Unpaired T-test is used to compare two normally distributed categorical variables that are independent of each other (Herzog, Francis, & Clarke, 2019). The null hypothesis for this test is that “means for the two observations are equal”. One-way ANOVA is largely similar to the Unpaired T-test but is used when there are three or more variables (Herzog et al., 2019). Similarly, the null hypothesis is that “means for the three and more observations are equal”. The Unpaired T-test is suitable for normally distributed data, while the Mann-Whitney test is used for non-normally distributed data. The main difference between the Unpaired T-test and the Mann-Whitney test is that the latter doesn’t make any assumptions about the type of the distributions of the two variables (Singh, 2007). The Wilcoxon Signed Rank test is also used in this thesis. It is used to compare two non-parametric categorical variables of the same subjects. The null hypothesis for these three tests is that “the difference score between the two population means is zero”. For all of these tests, if the p-value is less than alpha, then the null hypothesis can be rejected.

In correlation testing, Pearson’s correlation is used to analyze variables that are normally distributed, whereas Spearman’s rho is for variables that are non-normally distributed (Singh, 2007). A correlation coefficient value determines the strength of the relationship, while the sign of the value indicates the direction of the variable change, either positively or negatively correlated. The null hypothesis is that the correlation between two variables is not statistically significant, and if the p-value is less than alpha, then the null hypothesis can be rejected.

4 Results and Data Analysis

This chapter presents and discusses the data analyses from various stages of the research. The data were summarized based on the research actions and supported with pieces of evidence drawn from the analyses and were then discussed to answer the research questions posed at the beginning of this thesis. This chapter is divided into 3 sections: qualitative analysis, quantitative analysis, and discussion.

4.1 Qualitative Research: Content Analysis

The qualitative interviews were conducted over a period of 1.5 years via face-to-face meetings at agreed locations in Malaysia, Germany, and the Netherlands and online interviews using Microsoft Teams. The content analysis was carried out iteratively in conjunction with the interviews to determine the lower limit of the sample size. The sample includes participants with varying demographics, such as job positions, industries, companies, and continent of origin (Table 6).

Table 6: Interviewee Demographics

Continent of Origin	Job Position	Industry
European (8) African (1) South American (1) Asian (5)	Department manager (4) Project manager (3) Lead engineer (2) System engineer (4) Design engineer (2)	Automotive (7) Aerospace (5) Medical Device (3)

The sample size of the qualitative research is 15. The content analysis began after the completion of the first 7 interviews; the sample size gradually increased until the analysis hit data saturation when new themes no longer emerged (Francis et al., 2009; Morse, 1995; Vasileiou et al., 2018). Given the time constraints of the research, it was deemed practical to limit the interviews to 15 samples. The interviews were conducted in accordance with the interview guide (Appendix B). With a minimum of eight questions asked, the interviews yielded 304 condensed meaning units (Table 7) which summarize and highlight the participants' relevant responses to the questions. Some participants tended to deviate from the topic at hand, however, their responses could also be summarized into condensed meaning units when they provided additional insights into their decision-making processes.

Table 7: Content Analysis Summary

Participant	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Total
Condensed meaning unit	22	36	17	16	12	12	11	27	24	25	14	21	21	29	17	304
Code	16	23	15	14	9	11	10	22	18	20	14	14	16	22	13	68
Theme	9	11	8	7	6	7	8	12	10	10	9	8	8	9	7	14

The condensed meaning units (see Section 3.2.2.3) were classified into 73 codes. The codes were not specific to each participant because the underlying messages of their responses shared many similarities, and therefore could be group coded. The 73 codes were categorized into 14 overarching themes (Appendix D), but few of the codes did not belong to any of the themes because they were either the opinion of a single participant or were not relevant to the research topic. Some of the themes addressed a few of the research questions, while others shed light on unexplored tendencies in decision-making, such as risk appetite, and laid the groundwork for quantitative research, which can be found in Chapter 4.2. The findings from the qualitative data analysis were used to set up the structure of the quantitative research and to provide key points to be investigated.

Table 8 shows an overview of the nine themes to be discussed in this chapter. Only nine were selected because they accounted for the majority of the participant's responses and fulfilled the objectives of the qualitative research. Interviews were conducted in English with mostly non-native speakers and hence, in this thesis, responses were paraphrased based on the context from the surrounding statements wherever necessary to ensure clarity of meaning.

Table 8: Themes from Content Analysis

1	Technical decision-making is overwhelmingly a group effort. The group is involved to gather information, negotiate decisions and reevaluate previously-made decisions.
2	Not all organizations prescribe decision-making guidelines; when they do, the guidelines are normally not properly documented, and the level of detail is inconsistent
3	Analytical processes and personal judgments are both utilized during technical-decision making, although analytical processes are preferred
4	Decisions are rationalized with expert inputs, technical analysis, evidence, and feasibility studies
5	Personal judgment is used if the decision is simple, information is sparse, time is a constraint, or decision risk is low. Analytical processes are used if the decision is risky or critical if the analysis is complex
6	Inputs to decision-making processes are judged based on the completeness of information, quality, and relevance of information, and reliability of the information source and the information seeker
7	Personal judgment is used to choose an alternative from analytical process outputs, to test whether results fit with personal knowledge, and to judge whether the analytical process used may be unreliable due to incomplete information and objectiveness of the analysis
8	Alternatives are re-evaluated based on the technical risk of the decision, the driving requirements, the project's timeline and budget, and the organization's vision and resources
9	If new information deviates from current data, the impact analysis will be performed based on the cost and criticality of the decision context. Decision shall be adjusted if there is a severe impact on the project and team resource is available to execute the decision

4.1.1 Results & Analysis

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Theme 1: Technical decision-making is overwhelmingly a group effort. The group is involved to gather information, negotiate decisions and reevaluate previously-made decisions.

The content analysis showed that technical decisions in engineering organizations were normally made within a team, which comprised of information seekers, a coordinator, and decision stakeholders. The team was cross functional in nature to ensure that the decision made was robust and took into consideration multiple viewpoints.

Information seekers were subject matter experts in the decision context; they gathered and analyzed information from various sources. Any incoming information, regardless of the source, was reviewed by the team (Example 6). The team would ensure that the information fed into the decision-making process was correct and relevant to the decision context.

> *Participant C: […] we make the design reviews, sheets and work (using) this method. Basically this method has three steps and by each step we made <u>special reviews sections that the experts show us what he has thought</u>, what was evaluated and so on.*

Example 6: Expert inputs

The team coordinator was generally the decision owner, responsible for the decision made and supported by subject matter experts to gather and analyze the information to make technical judgments. Even though the coordinator held responsibility for the team's decision, it was observed in a majority of the responses that a decision based on group consensus was preferred (Example 7 and Example 8). When stakeholders of the decision were external to the decision-making team, their opinions and consensus were also sought.

Participant E: Decisions are typically based on either an analytical process or a collective agreement within the team. The team provides ideas, and our decisions are made based on them.

Example 7: Agreement of the team

Participant B: [...] First of all, anyone can weigh in if the decision does not align with his or her personal judgment on the topic, and also to generate consensus on that topic.

Example 8: Consensus on a decision

Technical decisions in the industry affect various stakeholders and impact many other decisions. Therefore, it was noted in the analysis that technical decisions were generally negotiated and not unilaterally decided (see Example 9). The balancing of stakeholder needs during the decision-making process required more than technical justification. The stakeholders had their priorities and needs, from commercial and organizational to technical points of view, and would pull the direction of the decision their way. It was then the task of the team to balance the needs of the stakeholders in order to reach a compromise (Example 10).

Participant M: Hopefully, the two approaches work together; otherwise, there's a lot of renegotiations. A large part of this job involves negotiating requirements. In fact, engineering decisions are often easier than dealing with the requirements and politics involved.

Example 9: Decision-making is a negotiation

Participant N: I would say the challenge always lies in balancing the various needs within the organization. For instance, choosing between the most reliable solution and the most desirable technical solution within a specific timeline.

Example 10: Decision-making is about balancing needs

Theme 2: Not all organizations prescribe decision-making guidelines; when they do, the guidelines are normally not properly documented, and the level of detail is inconsistent

The interviews showed that many organizations had decision-making guidelines, albeit with varying levels of detail and availability. The guidelines laid out methods and tools to be used in the product development process. The prescribed guidelines covered both technical and commercial decisions. Some of the technical decision-making guidelines focused on identifying the criticality of a decision and the selection of conceptual design. They were in place to ensure the decision-making process was consistent across organizations and the robustness of the decision met the organization's quality standards and industry norms. The availability and quality of the guidelines might vary between organizations.

All participants' organizations prescribed at least a basic level of product development guidelines to be followed. However, guidelines specific to technical decision-making were often not made available in every organization (Example 11). Even though decision-making tools were not necessarily prescribed by the organization, design reviews were mandated by many organizations to ensure technical decisions were deliberated and documented systematically.

> *Q: Does your organization prescribe technical decision-making methodologies or guidelines?*
>
> *Participant F: No. Essentially, we don't have a fixed methodology. Everyone is encouraged to contribute ideas regarding which methodology could be used, based on the situations we encounter. Any relevant methodology is accepted; we do not adhere to one specific approach.*

Example 11: No decision-making guidelines available

Decision-making guidelines were not always specified in detail (Example 12), and the levels of detail would also vary depending on the decision context. The few guidelines that were made available would propose concept selection tools to be used; but in many cases, it was left to the team to decide the decision-making methodology to be used based on the situation at hand (Example 11).

Participant M: The [decision making guidelines] document initially started very broadly. However, it becomes evident that starting with a broad approach inevitably means that you have to narrow your focus in certain areas as you proceed.

Example 12: Decision-making guidelines are broad

In many high-risk but routine decision-making situations, such as product manufacturing and procurement, specific guidelines and problem-solving tools were prescribed (Example 13). However, this might not be the case with technical design decisions, despite the fact that many of the decisions were risky in nature. Furthermore, the design process required a high level of creativity. Therefore, detailed design guidelines would stifle innovation and are counterproductive to the product development process (Example 14).

Participant I: For procurements, there are very specific guidelines. [...] Everything related to procurement, I believe, adheres to strict guidelines regarding how to select different suppliers and how to assign contracts, etc.

Example 13: Procurement decision-making

Participant M: When we actually initiated it, we had to delve quite deeply into certain areas. However, it's not mandated to be detailed in all areas because design inherently involves innovation, and innovation is somewhat of an art form. You don't want to inhibit that, as doing so might prevent achieving the best designs.

Example 14: Decision-making guidelines stifle innovation

Theme 3: Analytical processes and personal judgments are both utilized during technical-decision making, although analytical processes are preferred

While the product development process was regulated by standards and guidelines, the interviews showed that decision-makers also used personal judgment to make technical decisions. Rule-following was the normative decision-making process in engineering organizations, and in reality, the decision-makers adhered to the rules and guidelines as required. However, rational analysis, via the use of analytical tools, was the preferred method by a majority of the participants to drive the decision-making process (Example 15). In some instances, decision-makers would also rely on their personal judgments to make the final decision. Analytical methods and human judgments both played roles in decision-making based on their respective strengths and shortcomings.

Participant E: Personal judgment often leans more towards emotional decision-making and can sometimes be difficult to justify, while an analytical approach is generally the more appropriate course of action.

Participant F: In my past experiences, I've consistently adhered to one methodology that I've found to be quite relevant and efficient: the decision matrix.

Example 15: Analytical approach is preferred

Analytical tools were mainly used during the product development process, especially during problem-solving, risk analysis, and decision-making (Example 16). In high risk decision contexts, impact analysis was used to systematically establish and analyze the risks (Example 17). Analytical processes were perceived to be efficient in narrowing down problems or identifying effective solutions. Some participants felt that, where feasible, it was the most reliable method to approach technical decisions (Example 15).

Participant L: [...] What I need to do is initiate a problem-solving methodology, where I adhere to a six-step process, such as defining the problems and then taking interim actions to ensure that our current issues do not become more damaging. Subsequently, we try to identify the potential root cause.

Example 16: Root Cause Analysis as an analytical tool

Participant D: The first thing that comes to my mind is that typically, when dealing with changes—something that will cause an impact—we definitely need to consider the impact analysis, whether technically, commercially, etc.

Example 17: Impact Analysis as an analytical tool

A few participants preferred to make decisions based on their knowledge and experience. They relied on their intuition, which is a sub-conscious decision-making process, and knowledge of the subject matter (Example 18). This behavior was most commonly noted among experienced decision-makers. However, in many cases, decision analysis would assist in systematically organizing, analyzing, and ranking the solutions based on the weighted criteria, and decision-makers then relied on their personal judgments to make the final decision (Example 19). The ranked solutions were subjected to a trade-off discussion between the stakeholders and subject matter experts (Example 20). Consequently, the decision analysis might not be as objective as intended since decision-makers would alter the objectively-driven process according to their subjectively influenced personal preferences and agendas.

Participant M: [...] All of those decisions, whether through innate ability or experience (and I can't specify which), are made subconsciously without my active deliberation.

Example 18: Technical decision-making based on experience

Participant C: I believe it's always a combination; no decision is based solely on an analytical process or methods. The decision should incorporate the insights and intuitions of the experts.

Example 19: Concurrent technical decision-making

Participant N: [...] Let's say there are top three options that are closely ranked; you might still employ some personal judgment within a smaller team. But in principle, you would simply select the number one solution as it's the most logical choice.

Example 20: Decision-making as a trade-off

Theme 4: Technical decisions are rationalized with expert inputs, technical analysis, evidence, and feasibility studies

Even though rationality in the actual technical decision-making process was not fully optimized (see Section 5.2, Theme 3), it was apparent from the interviews that all engineering decisions must be technically justified. Industry standards for product development processes, such as in the automotive, medical device, and space sectors, require design reviews to be conducted at predetermined checkpoints during product development. Technical justifications, which can be in the form of technical analysis, expert opinions, or feasibility studies, as evidence of thorough technical due diligence, form a major part of the design review. In cases where technical justifications were not necessary, decision-makers strived to ensure their decisions were justified.

Technical analysis, especially during the conceptual and design stages, is the backbone of any product development decision-making (NASA, 2007; Robert Bosch GmbH, n.d.).Technical decisions in product development – such as component or circuit design, material selection, and software algorithms – are rationalized using technical analysis (Example 21). The analysis includes tolerance or strength calculations, hardware-in-the-loop simulations, statistical analysis, design of experiments, and many more. Technical analysis not only supported technical decisions during the design review but also helped boost the confidence level of decision-makers in the design output phase (Example 22).

> *Participant O: In our technical decision-making, we evaluate whether we genuinely wish to verify aspects such as fit and function based on their functionality. We ponder whether we can do so using a virtual simulation platform or an analytical method.*

Example 21: Technical analysis examples

> *Participant J: [...] Confidence in whether your design will work can be gained through analysis. Deciding which direction to take and which options to focus on involves professional experience, drawing upon technological heritage knowledge, and considering the risks associated with any gaps.*

Example 22: Technical analysis increases design confidence

Expert opinions were also used to support technical decisions (Example 23). In contrast to quantitatively-oriented technical analysis, expert inputs were derived from their subjective evaluation of the decision context based on their knowledge of the subject matter. Expert opinions were highly valued as they were the main source of information, and their judgments were deemed reliable.

> *Participant C: I will select the best options from this analytical process, perhaps two or three, and invite the most knowledgeable experts I have on the subject, seeking a second opinion. Then we make a decision; I will decide based on this analytical process and feedback from other experts, attempting to reach a conclusion.*

Example 23: Expert inputs to support technical decisions

Theme 5: Personal judgment is used if the decision is simple, information is sparse, time is a constraint or decision risk is low. Analytical processes are used if the decision is risky or critical if the analysis is complex

The content analysis showed that although organizations prescribed analytical tools to help the decision-making process, using such tools did not come automatically for many of the participants. The participants tended to apply personal judgment instead of an analytical approach when the decision to be made was simple, the risk of the outcomes low, the information incomplete, the decision time limited, or available human resources scarce.

The complexity of the decision played an important role when deciding whether to base a technical decision on personal judgment or to use a systematic analytical process (Example 24). However, as the decision got more complicated, decision-makers tended to rely on analytical processes to gather relevant information and evaluate potential options. But when the decision was simple and straightforward, the decision was based on the knowledge and experience of the decision-maker.

> *Participant N: In cases of complex decisions, such as our examination into DCI connectors which presented various options, an evaluation was undertaken in*

2020 using a ranking process. This involved an eight-person team making the decision, necessitating the use of ranking tools.

Example 24: Analytical tools help to make complex decision

Moreover, if the information to make decisions was scarce, then the decision-makers would rely on heuristics to make the decision (Example 25). This reliance also occurs when there were insufficient resources, such as time and manpower, to make deliberative decisions. In cases where allocated resources were limited, decision-makers might be forced to make decisions based on their experience (Example 26). Since rational analysis is a resource-intensive process, a lack of human resources to gather information or carry out planned measures could be an obstacle. Time constraints could also compel decision-makers to make quick decisions that are prone to biases. Furthermore, they also had to rely on their instincts and knowledge if there was insufficient information to make an informed decision.

Participant B: It's also crucial to note that in the early phases of such decisions, the foundation may not be solid enough, as I pointed out using the ED&T costs example. In the initial stages, estimates can only be based on experiences or rule-of-thumb evaluations.

Example 25: Personal judgment for incomplete information

Participant H: I would assert that analysis is absolutely the foundation for all sound decision-making. Often, however, either time constraints or limited available manpower prevent us from performing it. Subsequently, decisions hinge on the expertise of individuals involved.

Example 26: Personal judgment for limited resources

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An analytical approach was also preferred if the stake of the decision outcomes and risk were high (Example 27). For example, decisions that may influence the organization’s strategic objectives that can cause a change of direction of the product development or that can severely impact the safety or functionality of the product are considered high risk. If the impact of the risk was relatively low, decision-makers might use either an analytical process or personal judgment.

Participant A: I would then employ an analytical approach, especially if the matter is also of a strategic nature. For instance, if there's a technical decision to be made that could alter the team's direction for the upcoming six months, I will ensure confidence in my decision before finalizing it.

Example 27: Analytical tools help to make critical decisions

Theme 6: Inputs to decision-making processes are judged based on the completeness of information, quality and relevance of information and reliability of the information source and the information seeker

Based on the interviews, it could be summarized that the decision-makers would evaluate all information before any decision could be deliberated. Any input data should first be verified and then filtered in accordance with the decision-maker's knowledge (Example 28). If the input information conflicts with the decision-maker's experience, the information would be questioned and cross-checked against other different sources.

Participant H: It's imperative to rely on your experience to determine whether the input you've received is credible and suitable for your use in the process.

Participant B: [...] We typically have six-month contracts; if we alter them to one-year contracts, I expect the monthly rate to decrease. If it doesn't, then it's something I need to investigate. This is sort of a rule of thumb, I'd say. If my experience indicates a consistent increase in prices, that's something I won't definitely accept [...]

Example 28: Input information is evaluated based on experience

Completeness of information is one of the criteria for achieving objective rationality. Even though decision-makers are subjected to bounded rationality in making decisions (Simon, 1955), they strive to gather as much information as possible to ensure the robustness of the decision. Each decision-maker would have a different threshold for the minimum amount of information required to make a judgment (Example 29). They would gather more information from historical databases, personal knowledge, and other sources if they thought the information provided was insufficient based on their knowledge.

> *Participant A: I'd identify two aspects: first, do I feel I have all the presently available information, which doesn't mean all possible information... there will always be, let's say, an element that you can't estimate because every decision involves some unknowns. But, if all the information that can be obtained without unreasonable effort is before me and I feel that is the case, then I proceed with the decision.*

Example 29: Incompleteness of information judged based on experience

The participants might also challenge the reliability of input data if the information is of poor quality. In general, the decision-makers would carefully gather the information according to their experience and knowledge of the subject matter. The input data would be accepted if it was aligned with their knowledge or if the information derivation process was judged to be reliable (Example 30). However, information from trusted subject matter experts was accepted 'as is', without further deliberation of its quality.

> *Participant A: There's also a significant trust component that should not be underestimated. So, depending on the messenger - if it's an engineer with whom I've had very positive experiences and whose competence I trust - I'll be more inclined to believe them.*
>
> *Participant B: And the manner in which they present how they arrived at that result is something I need to be able to accept. So, in this specific example, if, from my viewpoint, all necessary experts are involved and if I see that the work quality is commensurate with the topic's criticality, it's acceptable.*

Example 30: Quality information from a reliable source

Another factor in determining the acceptance of the input data is the credibility of the information source and the information seeker. The validity of the information would be confirmed if the decision-makers have any concerns regarding the reliability of the data source. Where the decision-makers had limited knowledge of a particular topic, they would often consult subject matter experts to ensure the data sources were providing high-quality information (Example 31). Furthermore, the credibility of the information seeker would also be called into question before the provided information can be accepted. The majority of the participants expressed confidence in the data presented by trusted subject matter experts, especially when the experts were from the same organization (Example 30).

> *Participant O: Certainly, the source of information plays a vital role. For instance, if a document originates from a trusted source like ASTM [American Society for Testing and Materials], UL [Underwriters Laboratories], any ISO [International Organization for Standardization] procedures, or EC [European Commission] guidelines, I'll prioritize those because they have been thoroughly evaluated and are generally reliable.*

Example 31: Trusted source of information

Theme 7: Personal judgment is used to choose an alternative from analytical process outputs, to test whether results fit with personal knowledge and to judge whether the analytical process used may be unreliable due to incomplete information and objectiveness of the analysis

Based on the analysis, it was rare that decision-makers accepted the output of decision analysis as it stood. They would ascertain the validity of the process, deliberate the outcomes of the analysis, and make their own decision guided by the analytical outputs. Decision-makers would only accept the analysis if the computed outputs aligned with their knowledge, or if they believed the analytical process was robust and the analysis had sufficient inputs to make a well-informed decision.

In general, the decision-makers valued their own knowledge and experience over analytical tools, such as decision analysis. Even when a decision analysis was used to objectively evaluate information and calculate the best possible outcomes based on the requirements and constraints, decision-makers would, in parallel, process the same information and make judgments of their own. They would use the decision analysis results when the ranked outputs were aligned with their own.

Decision-makers generally already had their own preferences, and decision analysis was mostly used to justify their decisions.

Participant C: If you possess sufficient experience [...] and the options from an analytical process don't align with what you have learned or encountered previously, I believe that a person will never accept the decision from any analytical process.

Example 32:Preference of personal knowledge over analytical tools

Participant H: Those involved in decision-making often suggest having a trade table or matrix. They recommend applying weighting factors and attempting to compare various solutions against each other. However, this has never been executed in real life. It's a purely theoretical example because one can always immediately find a reason why one solution is superior to another.

Example 33: Decision already made up

Decision-makers would not only selectively choose input data based on the completeness of information (see: Theme 4) but they also doubted the reliability of conclusions drawn via decision analysis that was made based on insufficient information. Technical decision-making is an information-loaded process as it requires large quantities and high quality data to make robust judgments. The analytical process produces logical analysis and objective evaluation, but the quality of the process is dependent on its inputs (Example 34).

Participant D: To me, it essentially boils down to the data set that has been input into the tools. I believe if the data set is substantial and covers enough areas, then I would say the tools will likely produce a strong recommendation.

Example 34: Insufficient information results in poor analysis

The robustness of an analytical process depends on the quality of the tool and the method in which the process is applied. Not all analytical processes or tools are made equal; they differ in objectivity and depth of analysis. The outcome of the analytical process should be objective; however, some users would strategically manipulate the tools to produce outcomes that they desire (Example 36). Moreover, some analytical tools are more suited to a specific decision context than others. Complex decision contexts require more holistic and robust analytical tools (Example 35). Therefore, decision-makers are inclined to be wary of the reliability of analytical tools outputs.

> *Participant B: It’s contingent upon the quality of the outputs. [...] If the process provides reasoning behind the ranking and also demonstrates alignment with my engineering expertise, I could see myself trusting the results, especially for technical changes. [...] How comprehensive is the process? When discussing an analytical process, which aspects do they actually consider during the analysis? Is it solely technical? Purely commercial? Exclusively about customer compatibility? Strictly strategic? If so, I'm skeptical.*

Example 35: Analytical tools should have a holistic view of the problem space

> *Participant N: By the way, what I observe in those ranking processes is that they seem very objective, but they never are. If you're in a joint ranking process, you will always observe behaviors like, if after the initial rankings, preferred solutions of some participants rank too low on the list, people then begin to strategically rank based on other factors.*

Example 36: Analytical tools are not truly objective

Theme 8: Alternatives are re-evaluated based on the technical risk of the decision, the driving requirements, the project's timeline and budget, and the organization's vision and resources

It was found from the interviews that decision-makers tended to make the final decisions even when decision analysis was used to generate a ranking of alternatives. Even though they believed decision analysis was the superior method, their biases would steer them to choose the alternative that fitted their knowledge. When presented with the alternatives, decision-makers based their final judgment on the decision risk, key requirements, project constraints, and organizational strategies.

Participants' technical decisions were largely driven by the decision risk and key requirements. Striking a balance between fulfilling key requirements and managing technical and commercial risks was the practice in the technical decision-making process (Example 37). A majority of the participants preferred alternatives that prioritized project risks and key requirements even though decision-making selection criteria would specify otherwise.

> *Participant O: Utilizing professional judgment is imperative to determine the optimal design or technology selection. At a fundamental level, it's essential to revisit the requirements. The primary aim is to choose the most affordable and familiar technology, but if that doesn't adhere to your constraints, exploring more advanced technologies that do fit within your limits may be necessary.*

Example 37: Requirements drive the decision-making process

Limitations on technical decisions were often imposed in the form of project constraints and organizational strategies. Not only did organizations put constraints on project delivery timelines, but availability and capability of manpower could also constrain the project execution (Example 38). Therefore, complex solutions may have been deemed undesirable even when they were technically sound. Organizational strategic decisions could limit potential technical solutions.

> *Participant L: We also strive to consider the team's capacity, because most of the time, there are numerous tasks to accomplish in a limited timeframe. Consequently, we certainly will not examine all of the items listed under the Pareto.*

Example 38: Project constraints on the decision-making process

Theme 9: If new information deviates from current data, the impact analysis will be performed based on the cost and criticality of the decision context. Decision shall be adjusted if there is a severe impact to the project and team resource is available to execute the decision

The content analysis indicated that a majority of technical decision-makers were risk averse and they would always re-evaluate current decisions when presented with new information. As discussed previously, organizational decision-making was a longitudinal process. Due to the interconnected nature of organizational decision-making, decisions made in other parts of the organization resulting in new information may have altered the direction of other decisions. This qualitative analysis earlier showed that decision-makers would analyze current decisions based on the impact criticality of the new information. If the impact was deemed to be severe and resource was still available, a new decision would be deliberated.

Participants in the interviews unanimously agreed that all new information should be treated seriously, and an impact analysis should be done to evaluate its effect on the current decision. This was particularly true if the information contradicted currently available data. The relevance of the new information and its impact on the success of the project were analyzed with the support of subject matter experts and stakeholders. When the impact was deemed to be critical to the success of the project, a new decision-making process would be executed (Example 39).

> *Participant F: If new information contradicts existing data, we certainly need to conduct another analysis. However, if the new input aligns with previous decisions, a new analysis may not be necessary.*
>
> *Participant D: Once a decision has been made and a change arises, the initial step involves evaluating the changes in aspects like cost, timing, and specifications. In my situation, the subsequent action is to decide how we should approach these changes, guided by the impact analysis*

Example 39: Impact of new information

When the decision-making team had concluded the severity of the impact of the new information, a new decision would be deliberated and implemented depending on the level of severity and if there was sufficient time and workforce available to execute the new decision. While a majority of the participants agreed that new information should be thoroughly evaluated, not all decisions were followed up. Most of the participants would only act if the outcome negatively impacted the project in terms of functionality, performance, or safety (Example 40). The availability of time and resources could hinder the implementation of the new decision. If there was insufficient time to act on the critical information, for example, if the project was nearing its end, then updating a decision may not have been possible (Example 41).

Participant M: Consider a scenario where it's discovered that the aluminum, perhaps due to the foundry or minerals used, is not suitable for space applications. A switch to stainless steel is necessary. This change will significantly impact as the weight implications will permeate throughout the project.

Example 40: Severity of the impact is a critical factor

Participant N: If you are nearing the end of a program and the change only affects a minor part of the program, you may opt not to modify it further. However, you could decide to either withdraw the solution or proceed with its release, even if some inferior parts fail.

Example 41: Not every important decision can be changed

4.1.2 Summary Findings

Based on the nine themes above, key findings in the qualitative research can be summarized as follows:

- Cognitive and social biases exist in the technical decision-making process (All themes, except for Theme 1)
- Information processing biases occur as decision-makers rely on their experience to filter information (Theme 6).
- Alternative selection biases affect decision outcomes because decision-makers rely on their intuitions for final decisions (Theme 7 and Theme 8).
- Alternative selection biases cause decision-makers to objectively re-evaluate decisions in light of new information (Theme 9).
- Risk appetite affects the decision-making process (Theme 5).

The Synthesized Model of Technical Decision-making in Product Development (Figure 37) was formulated by integrating the decision context (Figure 21) into the unified model of technical decision-making (Figure 23). In accordance with the general model of the design development phase in product development (Figure 21), the technical decision-making process in product development incorporates product requirements, available solutions, and other pertinent information as inputs into the process. Project personnel and budgets are also taken into account as constraints, while decision management and risk management govern the entire process. The synthesized model is a descriptive model describing the dynamics between rational and behavioral elements in the technical decision-making process within product development. The key findings contributed to the behavioral elements in the synthesized model. Cognitive biases, social biases, and risk appetites represent the human factors, or behavioral elements, that impact the technical decision-making process. Since organizational decision-making is embedded in a longitudinal context (Shapira, 2002), decisions previously made during product portfolio management or stakeholder requirement definition, as illustrated in Figure 21, might have already been biased. This biased information could inadvertently influence the technical decision-making process. The model and summary of findings from qualitative research laid the foundation for developing the quantitative research instrument, as discussed in Section 3.2.3.3.

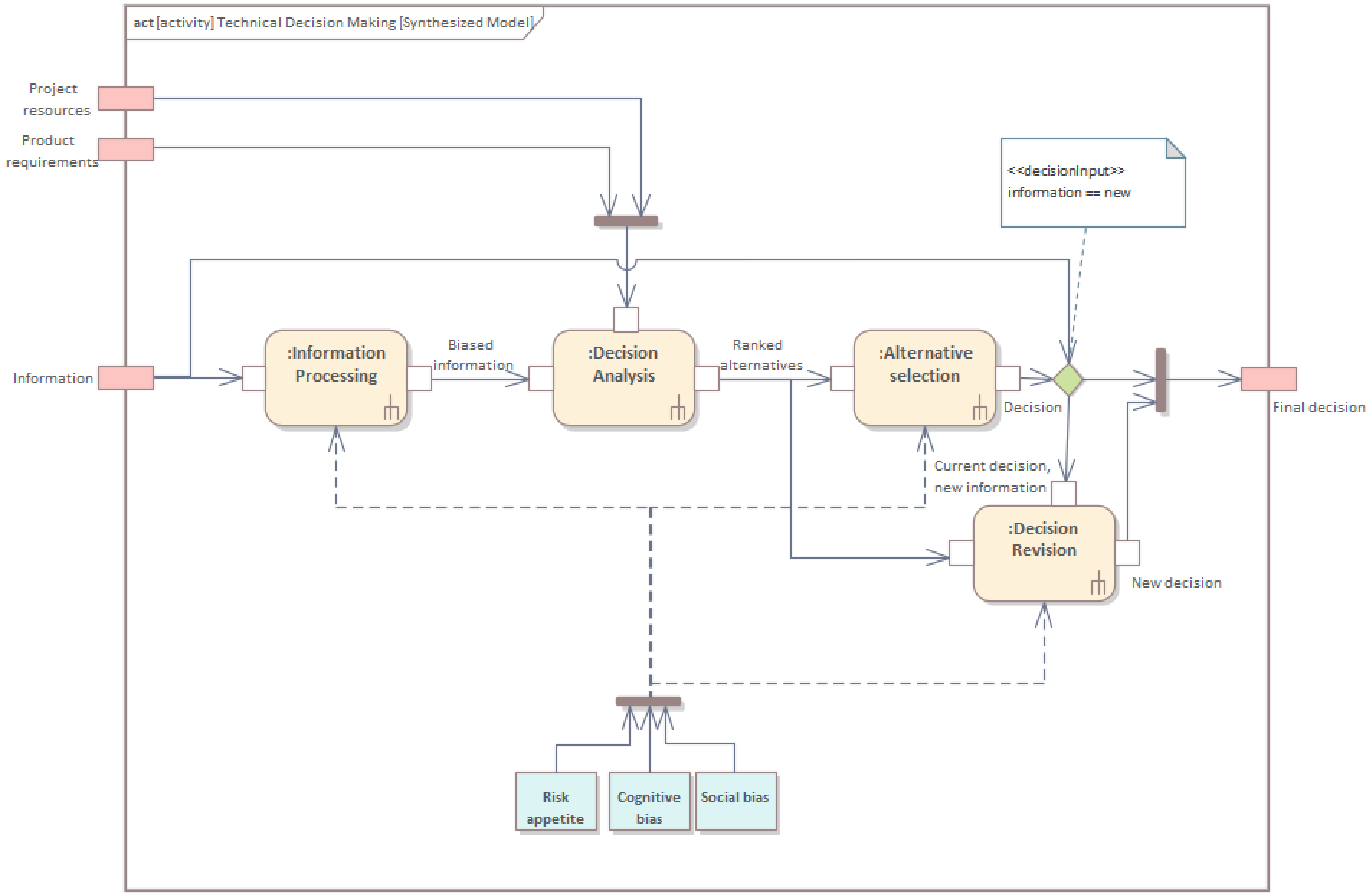

Figure 37: Synthesized Model of Technical Decision-making in Product Development

4.2 Quantitative Research: Exploratory Data Analysis

The survey was conducted over a period of two years via an online questionnaire (www.qpointsurvey.com) and an offline questionnaire (electronic copy of the questionnaire). In total, 132 responses were received with varying degrees of completion. After preparing the data (see Section 3.2.3.4), 96 responses were deemed suitable for use in statistical data analysis.

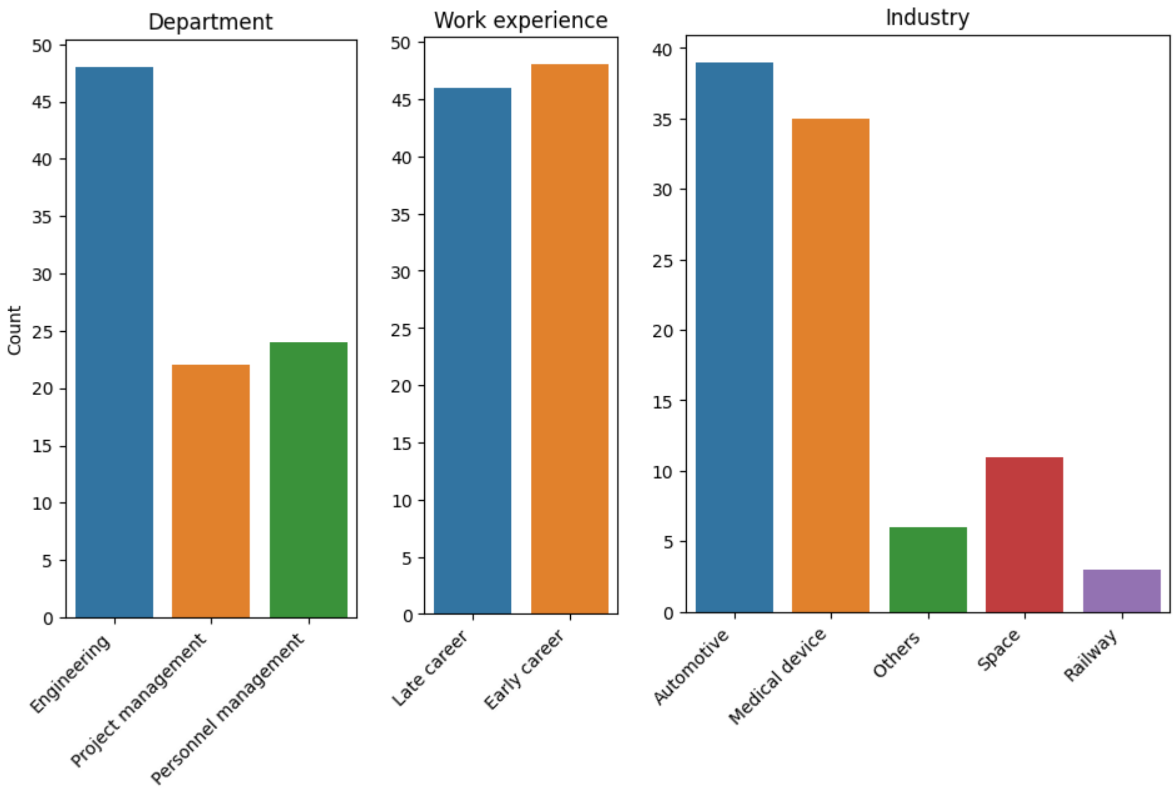

Figure 38: Quantitative research participant demographics

The demographics of the participants were divided into 3 categories: department, work experience, and industry (Figure 38). However, only department and work experience were used in the statistical analysis as independent variables. *Industry* variable was used to filter out participants who were not within the target demographics, which is safety-critical complex system industries.

Fifty percent (50%) of the participants worked in the engineering department as a development engineer, subject matter expert, system engineer, or other positions. Meanwhile, more than 20 participants worked in either project or personnel management departments. Furthermore, the respondents were split into two roughly equal-sized sets based on experience. ‘Early career’ respondents were respondents with 13 years or less job experience, whereas ‘late career’ respondents had more than 13 years of experience. Finally, the bulk of respondents worked in the automotive and medical device industries, with these industries together accounting for more than 70% of all responses. Space, railways, and other industries made up the rest of the responses.

The data was analyzed using Exploratory Data Analysis which presents data patterns between the variables. Full data with numbers and figures can be found in Appendix F. As quantitative research is a numerical approach to empirical analysis, bias strength in this section was quantified in Table 9. Table 9 is a synthesis of Table 3: Bias strength definitions) and Table 4: Data conversion).

*Table 9: **Bias strength score***

Bias strength	Definition	Score
Strong	Participant clearly demonstrates bias	4
Somewhat strong	Participant demonstrates noticeable bias with mitigating factors	3
Somewhat weak	Participant demonstrates subtle bias, with a lean toward impartiality.	2
Weak	Participant minimally demonstrates bias	1

4.2.1 Results & Analysis

Result 1: Decision-makers were overall moderately biased during technical decision-making

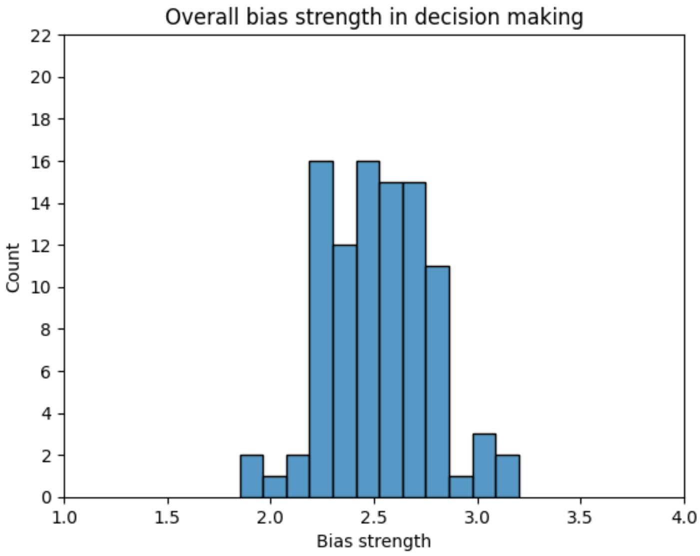

Figure 39: Overall bias strength analysis in the technical decision-making process

The mean value of overall bias strength in technical decision-making among the participants was 2.52 (Figure 39, Appendix F). The result can be inferred to as moderately biased, as the score lies between bias strength 2, which corresponds to "participant demonstrates noticeable bias but somewhat restrained" and bias strength 3, "participant demonstrates subtle bias, with a lean towards impartiality" (Table 9), which will be discussed in Section 4.3. The small dispersion of the data, with a standard deviation of 0.248 and interquartile 25th and 75th percentile values of 2.39 and 2.65 respectively (Appendix F), indicates that there was a slight variation in participants' bias strength. Furthermore, with a minimum score of 1.85 and a maximum of 3.2, one may conclude that no participant was strongly or weakly biased in the technical decision-making process. Decomposing the overall bias strength score into its components provides a better understanding of the phenomenon, as discussed in Result 2.

Result 2: The bias strength of decision-makers varied during the stage of the technical decision-making process

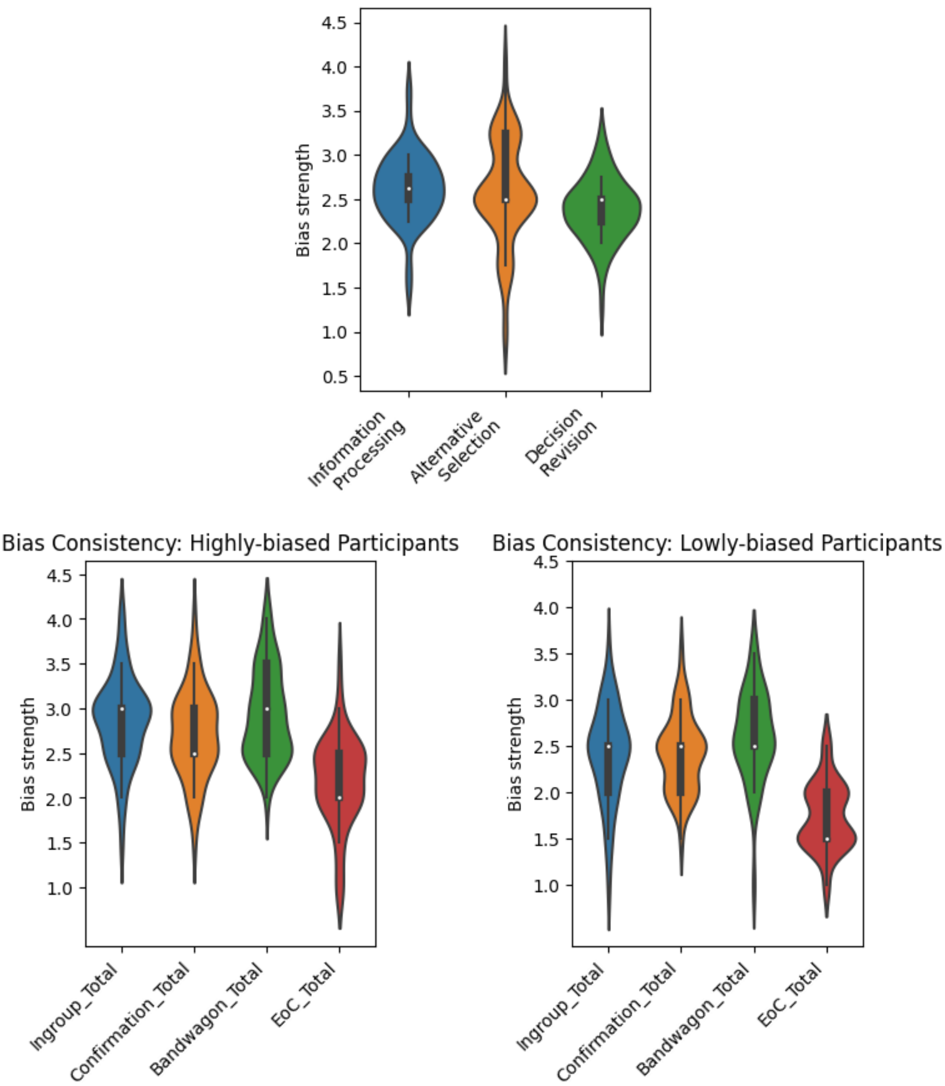

Figure 40: Bias strength per bias clusters

The overall bias strength score was composed of three components: information processing, alternative selection, and decision revision (see data variable structure in Figure 31). As discussed in Section 4.1, these biases influence different stages of the technical decision-making process. Results of the bias strength during information processing and alternative selection stages of decision-making were close, with mean values of 2.63 and 2.58 respectively (Figure 40, Appendix F). During decision revision, participants seemed to be slightly less biased compared to the other two stages based on their calculated mean value of 2.39 (Appendix F). Furthermore, participants with overall low bias inclination also consistently scored a lower bias rating per each bias than the participants with high bias inclination (Figure 40). Skewness or asymmetricity of alternative selection bias strength data, with a skewness value of -0.33 (Appendix F), toward strong bias is a point of interest. This can be explained with an in-depth analysis of the alternative selection process, as discussed in Result 3 below.

Result 3: Decision-makers most often make technical decisions as a team

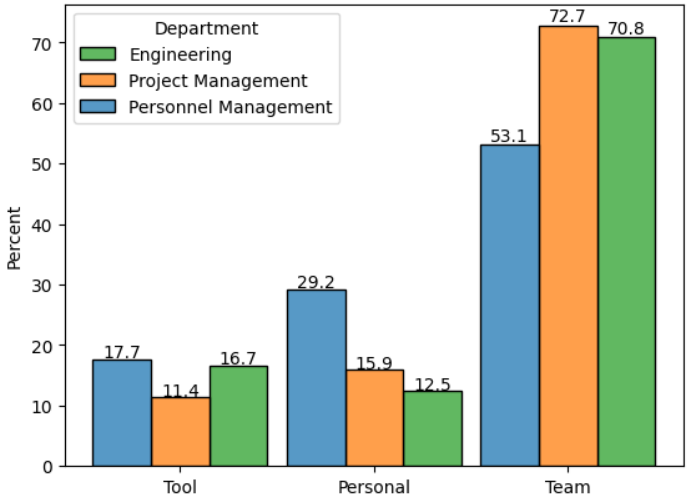

Figure 41: Decision-making preference

From the data analysis (Figure 44), a vast majority of participants did not make final decisions based on analytical tool recommendations; they either depended on team consensus (62.2%) or relied on their personal judgments (21.8%) to make the decision. Participants who worked in project management and engineering departments relied more on team decisions, with 72.7% and 70.8% respectively, than those in personnel management department, with 53.1%. However, participants in the leadership roles or those who worked in the personnel management department, tended to make more final decisions personally, accounting for 29.2% of the subgroup population, when compared to participants in other departments. Even though participants on average were hesitant to base the final decisions on analytical tool recommendations, participating engineers still slightly favored using the recommendations (16.7%) over making personal decisions (12.5%). In this thesis, the reasons behind participants' hesitation were also analyzed in Result 4.

Result 4: Decision-makers were skeptical of the robustness of decision analysis

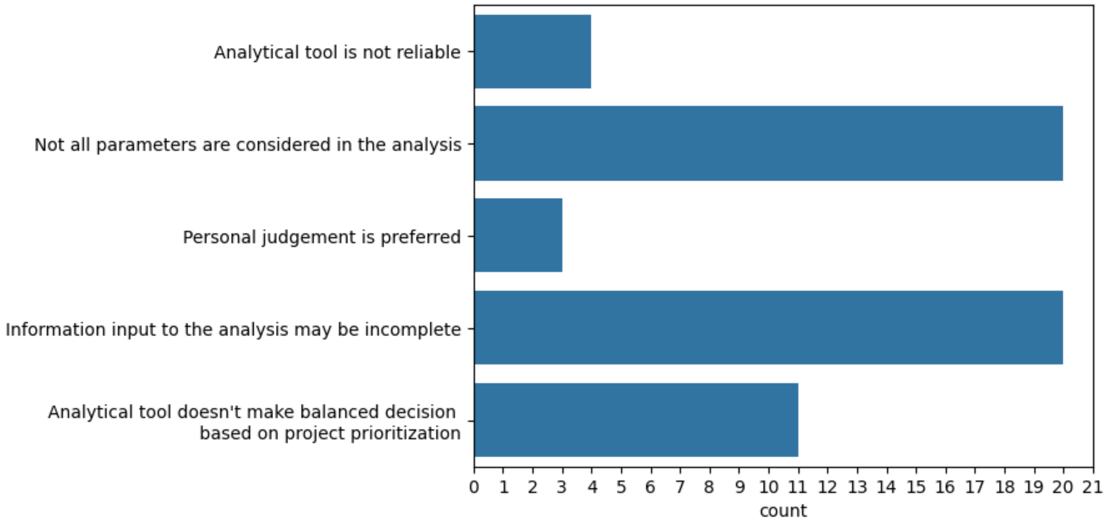

Figure 42: Rationale for not choosing analytical tool recommendation

In the questionnaire, the participants who opted not to accept decision analysis tool recommendations were asked for the rationale behind their decisions. They could either choose one or more responses from the predetermined choices or provide their own opinion (Figure 42). 20 participants did not think that all parameters were considered during analysis or felt that the information fed into the analytical tools was incomplete. Furthermore, 11 participants did not believe that the tool could make balanced decisions based on the project priorities. Additionally, four participants considered the analytical tool as an unreliable decision-making method, while another three participants preferred relying on their own judgment to make the final decision. While many participants argued that the analytical tool did not have sufficient information to make a rational decision, their tendency to not gather as much information as possible during decision-making, which is demonstrated in Result 5 below, contradicted their argument.

Result 5: Decision-makers did not require completeness of information to make technical decisions

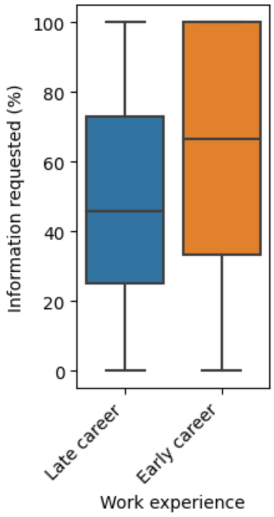

Figure 43: Tendency to request for information

In the questionnaire, specifically within sub-questions Q1, Q2, Q5, and Q10, participants had the option to request up to 12 additional pieces of information related to the questions before making decisions. Responses were systematically tracked and tabulated. On average, participants requested merely 56.8% of the available information (Figure 43, Appendix F). A deeper analysis of the data revealed that early career participants were more likely to request additional information (63.9%) compared to their late career counterparts (49.5%) (Figure 43, Appendix F). Utilizing the Mann-Whiteney test to examine the mean difference between two unpaired non-parametric variables, a statistically significant mean difference was identified between the early and late career participants' tendencies, evidenced by a p-value of 0.03. Furthermore, the participants who answered "Information input to the analysis may be incomplete" in Result 4 requested 56% of the available information on average, the same amount as the full set of respondents.

Result 6: There were no statistically significant differences in bias strength between participant demographics

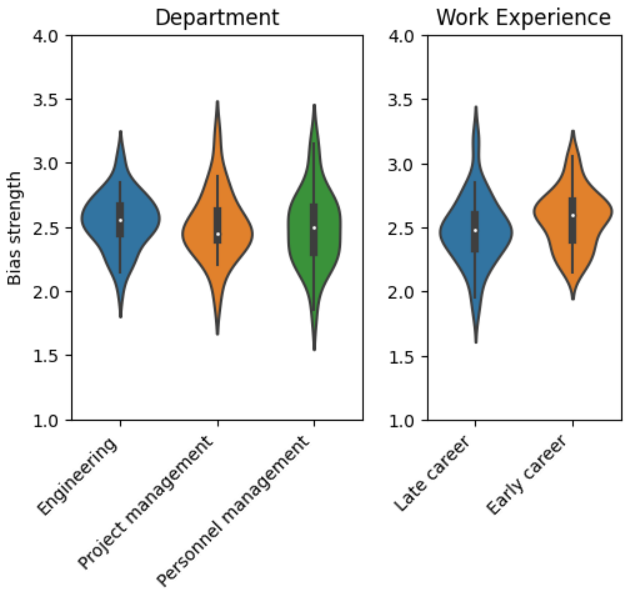

Figure 44: Bias strength per demographic subgroups

Figure 44 compares bias strength between subgroup demographics, i.e.: department and work experience. The mean bias score for participants from the engineering department was 2.546 while those from personnel and project management scores were 2.492 and 2.508 respectively (Appendix F). Testing with One-way ANOVA, which is a test for the mean difference between three or more independent normally distributed variables, the mean difference between the three departments was *not* statistically significant with a p-value of 0.75. As for work experience, late-career participants had a mean bias score of 2.48, while early-career participants' mean bias score was 2.57 (Appendix F). Two-tailed Unpaired T-test result, which tests for the mean difference of two unpaired normally distributed variables, with a p-value of 0.07 demonstrates that the difference was also *not* statistically significant with a 95% confidence level. Based on these data, one can conclude that the demographics of the participants have little effect on the strength of their biases during technical decision-making.

Result 7: Technical decision-makers were more prone to social bias than cognitive bias

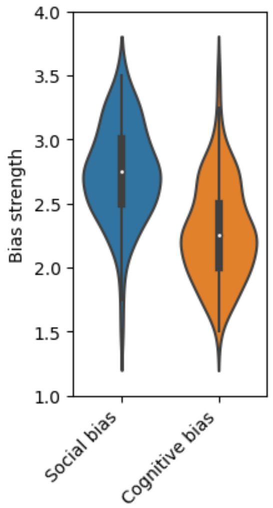

Figure 45: Comparison between the strength of social bias and cognitive bias

It was concluded previously that the majority of the participants relied on team consensus to make final decisions. The survey further probed into the social and cognitive biases of the participants to understand if these biases played a role in the decision-making process. The result (Figure 45) demonstrated that the participants had a stronger social bias, such as in-group bias and groupthink, with a mean score of 2.74 as compared to cognitive biases, such as confirmation and escalation of commitment biases, which had a mean score of 2.28 (Appendix F). According to the Wilcoxon Signed Ranked test result, which tests for the mean difference between two non-parametric categorical variables of the same subjects, the mean difference was statistically significant with a p-value less than 0.05. This result showed that the participants tended to be more biased during group decision-making but were less biased when making decisions alone. However, the data analysis (Result 8) showed that team setting was not the only factor that affected the decision-maker's bias tendency.

Result 8: Technical decision-makers were risk-averse

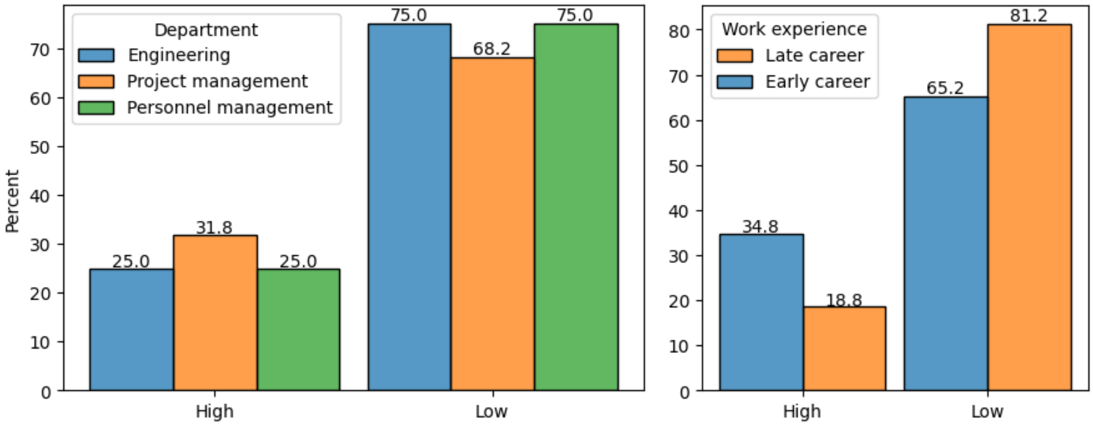

Figure 46: Participant's risk tolerance level according to department and work experience

Qualitative research found that risk appetite may affect decision-maker’s bias tendency. So, the questionnaire was constructed to test and verify this finding. A sizeable majority (73.4%) of the participants demonstrated low-risk tolerance (Figure 46). Early-career participants tended to have a much lower risk tolerance level (18.8% vs 34.8%) than late-career participants, while participants who worked in project management had a considerably higher (31.8% vs 25%) risk tolerance than their counterparts.

Result 9: Risk tolerance of technical decision-makers correlated with their bias strength

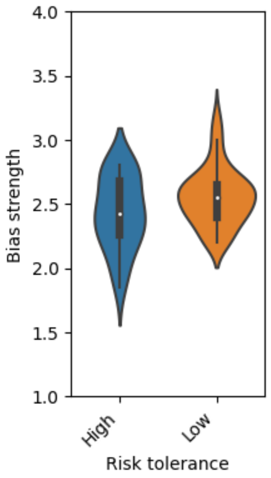

Figure 47: Participants' risk tolerance effects on bias strength

The relationship between risk tolerance and bias strength was also assessed. Analysis of the data (Figure 47) showed that high-risk tolerance participants appeared to be less biased, with a mean score of 2.47 than their low-risk tolerance counterparts, with a mean score of 2.56 (Appendix F). This was supported by the result of the Two-tailed Unpaired T-test, which demonstrated a statistically significant mean difference with a p-value of 0.03. The effects of the technical situation's risk level on the participant's bias strength were also tested (Result 10).

Result 10: The technical risk level of a decision context doesn't affect decision-makers bias tendency

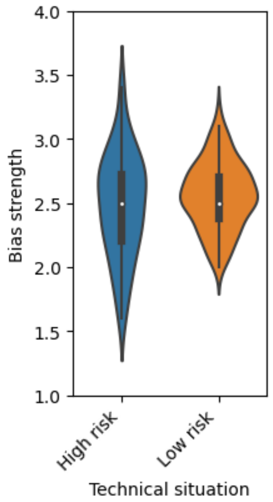

Figure 48: Technical situation's risk level effects on bias strength

The technical situation's risk level did not seem to have much effect on the decision-maker's bias propensity (Figure 48). The mean bias strength of the participants who were subjected to low technical risk situations was 2.56 which was slightly higher when subjected to high risk situations, which was 2.49. However, the Two-tailed Paired T-test result of the data showed that the mean difference was *not* statistically significant, with a p-value of 0.18.

4.2.2 Summary Findings

Based on the ten results above, key findings in the qualitative research can be summarized as follows:

- Participants were moderately biased in technical decision-making (Result 1).
- Participants seem to be slightly less biased during decision revision compared to the information processing and alternative selection stages (Result 2 & Result 3)
- Participants tend to be more biased during group decision-making but were less biased when making decisions alone (Result 7)
- High-risk tolerance participants appeared to be less biased than their low-risk tolerance counterparts (Result 9)

4.3 Discussion

Despite the availability of objective-driven procedures for making technical decisions, the interviewees still exhibited biases in their decision-making processes. The qualitative research results suggested social and cognitive biases can be found in technical decision-making. Biases distort information processing, affect alternative selection, and influence decision revision. The data analysis also concluded that behavioral components, such as heuristics and biases, were deeply embedded in the rationally oriented technical decision-making process. Quantitative research was built on the results of qualitative research by quantifying the deviation between rational and behavioral components in technical decision-making and identifying the root causes of the deviation. Therefore, this section addresses sub-research questions (RQ1.1, RQ1.2, RQ1.3, and RQ1.4) by combining the research data to provide full insight into the technical decision-making process.

RQ 1.1: What decision-making methodologies do engineering organizations expect for technical decisions?

Normative decision-making explains how people or organizations *should* behave to achieve optimal decisions (Rechtin & Maier, 2000; Simon, 1972). In the literature, rational behavior is the center of normative decision-making as normative decision theory revolves around mathematical models such as game theory and decision analysis (Fox, 2015; March, 1978; Over, 2008). However, this thesis has discovered that normative decision-making in engineering organizations, especially those within safety-critical complex system industries, emphasizes rule following instead.

Decision analysis has been studied over the years, dating back to as early as 1968 through a publication by Howard Raiffa (Raiffa, 1968). Since then, scholars have proposed numerous decision analysis methodologies, such as influence diagrams or decision networks (Howard & Matheson, 2005), multi-attribute utility analysis (Keeney & Raiffa, 1993), Simple Multi-Attribute Rating Technique (SMART) (Edwards, 1971), decision tree analysis (Raiffa & Schlaifer, 1961), and the analytic hierarchy process (Saaty, 1980). According to various studies, decision analysis has been employed in the industry to enhance the efficiency of engineering organizations' decision-making to varying extents (Hess, 1993; Krumm & Rolle, 1992; Ulvila & Brown, 1982). While the industry has been incorporating decision analysis as part of its decision-making tools, the results of this thesis concluded that the rational model is not necessarily the center point of normative decision-making in engineering organizations. Moreover, when deliberating between alternative solutions, the Systems Engineering Book of Knowledge (SEBoK) advocates for the inclusion of system analysis, effective analysis, or trade-off studies within the decision-making framework. Nonetheless, SEBoK acknowledges that "a decision-making process is not an accurate science," and therefore recommends that decision-makers exercise caution when applying subjective criteria and uncertain data to the decision analysis in their decision-making process (INCOSE, 2015).

Analysis of industry documents on how decisions should be made revealed that engineering organizations establish rules and guidelines for decision-making (Section 2.5). While rational decision-making is based on optimization and maximization of outcomes, rule-following decision-making is based on logic of appropriateness (Zhou, 2002). In rule-following, organizations prioritize the appropriateness of procedures over maximizing decision outputs (Carroll, 1994; Dobbin, 1994). This is in line with the thesis findings where technical decisions in the product development process are governed by a set of procedures and processes (Section 2.5.2). Then, depending on the product development phase and stakeholders involved, different types of technical decisions are to be deliberated and thus, different decision management strategies are required. Technical decisions in these organizations are determined by two processes: decision management and risk management (Section 2.5.2).

The document analysis shows that, at the industry level, decision management and risk management processes are described with a considerable level of detail as guidelines and procedures. Most of the guidelines specify analytical tools for decision-making and problem-solving, such as decision analysis or root cause analysis (Section 2.5.2). However, at the organizational level, the content analysis finds that the decision management process is often not provided with sufficient depth (Theme *2*). The analysis further showed that in many organizations, the level of detail in the guidelines is inconsistent and highly reliant on the decision context. While for other organizations, decision-making guidelines are not even explicitly stipulated. This is especially noticeable given that some of the organizational guidelines lack explicit details in requiring the use of analytical tools, such as decision analysis. For example, Theme *2* noted that specific tools are provided in the guidelines, but these are merely treated as suggestions instead of requirements. This is because the decision-making process is provided as guidelines, not standards. Standards specify organization-specific measurable requirements for processes, whereas guidelines offer recommended but non-mandatory supplementary guidance. Organizations may adopt decision-making guidelines suggested by their respective industries as appropriate (AIAG, 2008; VDA, 1998). However, adherence to industry safety standards is mandatory. These safety standards, though, do not explicitly compel the decision-making methodologies or tools to be used (ECSS, 2017; IEC, 2020; ISO, 2011).

The guidelines on process steps and actions are ambiguous and dependent on the interpretation of the decision-makers. Section 2.4.3 explains that decisions made through rule-following are subjected to the heuristics and biases of the developers and the users of the rules. When the users, or decision-makers in this case, are responsible for interpreting the guidelines based on their knowledge and understanding of the subject matter, the rationality of the decision-making process is their prerogative. This phenomenon can be explained in two ways: (1) organizations value efficiency over rationality (Zhou, 2002) and (2) loosely defined guidelines serve to facilitate a broad coverage of decision contexts (see Section 5.2 & Theme *2*).

Guidelines systematize the way of working while a systematic approach increases project efficiency. Despite the fact that rational decision-making is desired in technical decisions (AIAG, 2008; ECSS, 2009; NASA, 2007; VDA, 1998), rational analysis is resource-laden and time consuming (Simon, 1957; March, 1978). Therefore, organizations define decision-making process guidelines that allow for flexibility to the decision-makers (AIAG, 2008; VDA, 1998). Document analysis findings show that decision-making guidelines do not necessitate the use of analytical tools, so decision-makers are free to define their own decision management strategy and prioritize the strategy according to the project needs and risks involved.

Based on the document analysis of industry norms and guidelines, different decision contexts require different decision management strategies (ISO 15288, 2015). Decision-making guidelines are developed to ensure that they are flexible enough to adapt to a wide range of decision contexts. This is supported by the findings of this thesis. *Theme 2* postulates that if technical decision-making guidelines are too rigid by detailing every step of the process, it restricts decision-maker's capability to select the optimum decision-making strategy which in turn depends on the decision objectives, contexts, and boundary conditions. Rigidity in technical decision-making stifles innovation, especially during concept creation in the product development process. Flexible decision-making guidelines allow decision-makers space to think outside the box and thus rely on their intuitions and personal judgments to achieve the decision objectives.

In conclusion, this thesis suggests that normative technical decision-making process employed in organizations are not completely rational in nature. This research finds that rational analysis is not the *de facto* decision-making approach; but is highly recommended by decision-making guidelines, dependent on the decision contexts and agreement between the decision-makers. Decision-making through rule-following, as the dominant method in engineering organizations, strikes a balance between the desired rationality and the required efficiency of an organization. While the method strives for rationality in the decision-making process, allowing flexibility makes way for heuristics and biases to influence the process. Therefore, organizations should be aware of and carefully manage these unintended and possible side effects.

RQ 1.2: What decision-making methodologies are actually employed by engineering teams for technical decisions?

Descriptive decision-making explains how people or organizations *actually* behave to make decisions (French et al., 2006; Over, 2008). Literature dictates that the descriptive decision-making process predominantly operates under Herbert Simon’s bounded rationality (Dillon, 1998). Rightfully so, this thesis finds similar results where employees in engineering organizations actually employ personal judgments in conjunction with rational analysis when making technical decisions.

The bounded rationality concept posits that human rationality is bounded due to the fact that human nature has limitations in processing information and thereafter formulating and computing complex problems (Simon, 1956). Due to the limitations in human cognitive capability, individuals tend to pursue courses of action that meet their minimum utility requirements, rather than maximize them (Simon, 1956). In order to overcome the bounded rationality limitation, Kahneman and Tversky (1979) hypothesize, in their seminal descriptive theory for decision-making under risk, that people usually make decisions by editing and evaluating alternatives to simplify choice and "people normally perceive outcomes as gains and losses, rather than as final states of wealth or welfare". By relying on heuristics, people utilize minimal time and computation to make decisions (Gigerenzer & Todd, 1999)**.** While technical decision-makers in engineering organizations have been shown to exhibit a tendency to rely on heuristics and the prevalence of biases, they are also making use of rational analysis in their decision-making process.

The results of the content analysis demonstrate that rational analysis and personal judgment operate simultaneously alongside rule-following behavior as the guiding mechanism. As discussed in RQ1.1, the normative decision-making process in engineering organizations allows for flexibility for the decision-makers to balance the required efficiency and desired rationality. Decision-making guidelines only provide the basic foundation and structural support to guide them to make objective decisions; so, the decision-makers are expected to provide the details themselves. *Theme 3* of content analysis indicates that the usage of decision analysis and other analytical tools was prevalent among the decision-makers, especially in high-risk decisions. However, decision analysis would only assist in systematically organizing, analyzing, and ranking the solutions, in part because the decision-makers tend to rely on their personal judgments to make the final decision (Them*e 7,* Section 4.2). This is consistent with the literature where decision analysis should be used as a tool to assist decision-makers in making informed decisions; rather than making decisions itself (Wright & Goodwin, 2009).

Theme 5 suggests that decision-makers employ decision analysis and personal judgments interchangeably, contingent upon decision contexts, project constraints, and information availability. According to the literature, in highly complex decision scenarios, decision analysis is favored due to human limitations in formulating and computing complex problems involving numerous interdependent variables (Simon, 1957). Conversely, Theme 5 further alludes that the participants believed they could make more informed decisions using their intuition when the information provided was incomplete. In turn, they would gather more information if they thought the information provided was insufficient. This finding is in line with the study by Hutchinson and Gigerenzer (2005) which concluded that in situations with insufficient input data, making decisions based on heuristics proved advantageous. Thus, *Theme 3* explains that, in a majority of the cases, rational analysis and personal judgment were exercised in conjunction with each other.

Despite the fact that many participants agree that decision analysis leads to effective decision-making, they would still scrutinize the input data based on their knowledge and experience (Them*e 6*). The result shows the decision-makers evaluate all information introduced into the decision-making process, assessing the completeness, quality, relevance, and reliability of the source. As they process the information through the lens of their own experience and knowledge, their biases may potentially compromise the objectivity of the decision-making process. Wilson (2014) similarly observed this information-processing behavior in a study where people often ignore all but pronounced information or events, perceive information in line with their expectations, and are influenced by the order in which information is presented.

Concurrently, this thesis found that the majority of decision-makers did not make final decisions based solely on recommendations from decision analysis tools (Result 3, Section 5.2), but rather re-evaluated the tool-ranked alternatives based on the project's risk, requirements, and constraints (Theme 8, Section 5.1). They questioned the robustness of the tool (Result 4, Section 5.2), and therefore, preferred to render the final decision themselves. This skepticism supports existing research; given that numerous studies have underscored various challenges and limitations of decision analysis, including weak theoretical foundations, inadequate analysis by tool users, analyses often conducted from a specific perspective, and probability estimates being susceptible to bias (Dowding & Thompson, 2009; Goel et al., 1992; Keeney, 1982).

This thesis has further discovered that the decision-making process in an engineering organization was largely a group effort (Result 3). Information was gathered and processed, alternatives were generated and deliberated, and decisions were taken with the participation and agreement of project members (Theme 1). The complexity of technical aspects in product development necessitates decision-makers to engage in cross-functional teams to deliberate decisions. Decision-makers supplemented decision analysis by deliberating its outputs collectively within the team (Result 3), as they highly valued the opinion of subject matter experts (Theme 4). Theme 1 explains that a cross-functional team consists of information seekers, a coordinator, and decision stakeholders of varying knowledge and expertise, which supports the findings on the organizational decision-making team setup by Benne and Sheats (2010). The group's diverse knowledge and experience bring a wealth of ideas and critical viewpoints, which contribute to the team making robust decisions (George & Chattopadhyay, 2008). However, this may also inadvertently introduce undesirable social biases, such as groupthink and herd behavior, or create friction between team members (Janis, 1971; Robbins & Judge, 2001).

Based on the findings and arguments above, this thesis concludes that the technical decision-making process used in engineering organizations is both subtle and complex. It is akin to a three-way tug of war where rule-following, rational analysis, and personal judgment are pulling in different directions to reach an equilibrium point. None of the three decision-making methods can be deemed dominant, as the equilibrium point changes based on the decision context and organizational factors. Social and cognitive biases thrive in the kind of environment where personal judgments exist.

RQ 1.3: What biases exist in the technical decision-making process?

A total of 111 biases from the literature were identified and summarized (Section 2.5.3). The biases were analyzed and then integrated into the conceptual framework. This integrated framework proposed a unified model of rational and behavioral technical decision-making, where three bias clusters influence decision analysis: information processing, alternative selection, and decision revision (Figure 23). This unified model was validated by the findings in the qualitative analysis, where each bias cluster was shown to influence the technical decision-making process. Additionally, the qualitative analysis revealed that both cognitive and social biases are present in each bias cluster.

The academic community has shown increased interest in exploring biases in engineering decision-making. For example, Siefert and Smith (2011) investigated industry data, identifying several biases, including probability centering and consequence bias, which influence technical risk management in engineering organizations. Furthermore, Hallihan, Cheong, and Shu (2012), discovered the presence of confirmation bias during the stages of concept generation and evaluation. Also, Agyemang, Andreae, and Mccomb (2023) confirmed the existence of biases such as confirmation bias and overconfidence bias within engineering design practices, while also suggesting the potential presence of other biases like anchoring, hindsight, availability, and information. Having found similar results, this study delves deeper into the manifestation of biases within the product development process.

Decision analysis is an objective analytical tool that accepts input information fed by the decision-makers. Since the organizational decision-making process is longitudinal (Shapira, 2002), one cannot exclude the probability that the input information has already been biased in preceding decisions. In the literature, *biased information passing* was observed as a negotiation tactic by reporting conservative estimates to secure design margins in order to manage risk throughout the design process (Austin-Breneman, Yu, & Yang, 2016). In the content analysis, it was discovered that decision-makers exhibited some degree of information processing biases, where two biases were prominent: *confirmation bias* and *ingroup bias* (Theme 6). The analysis showed that decision-makers were skeptical of the information fed into the decision-making process. They would process the information, disregard those that are not aligned with their knowledge, and only accept information from sources they deem reliable. This behavior is aligned with definition of confirmation bias, where people are biased towards information that reaffirms their preexisting hypothesis and past choices, and discount information that undermines them (Klayman, 1995; Plous, 1993). Zheng et al., (2018) also verified the presence of confirmation bias in the concept selection process, with participants primarily seeking evidence that aligned with their existing beliefs. fg

Furthermore, *Theme 6* also showed that the decision-makers favored and readily trusted information from in-group sources, such as subject matter experts within their organization. They were skeptical of out-of-group sources of information unless it was from a credible source such as international regulatory bodies or industry associations. This inclination to prioritize one's own group over the others can be attributed to ingroup bias as defined in the literature where ingroup bias is an individual's inclination to favor inputs from members of their own group over those of other groups (Mullen, Brown, & Smith, 1992).

Additionally, decision analysis is an analytical tool that processes information and empirically ranks alternatives based on decision objectives and constraints. As discussed in RQ1.2, the decision-makers did not completely depend on decision analysis to make decisions as they would prefer to make the final decision themselves. This can be seen in Theme 8 where the participants subjectively re-evaluated the ranked solutions from decision analysis based on different factors such as project risk and constraints. Theme 7 further shows that the decision-makers doubted decision analysis due to its robustness to make an informed judgment. In turn, they rely on their heuristics and biases. The findings indicated that participants often had pre-existing preferences and used decision analysis to validate their decisions. They were confident in their judgments, particularly when the data matched their expected outcomes. This is an indication of an *illusion of validity* bias, where decision-makers tend to choose an outcome based on its proximity and alignment with their expectations (Tversky & Kahneman, 1974).

As discussed in RQ1.2, technical decision-making in engineering organizations is a group effort. Theme 1, Theme 3, Theme 4, and Theme 6 of content analysis demonstrated that participants relied on their team to evaluate options and make final decisions. Result 3 of the exploratory data analysis verified the findings that decision-makers tend to conform to team consensus, a tendency that can be subjected to social bias. Another phenomenon that could have emerged and influenced the team's decision is groupthink where team consensus is required from the majority of the team members to agree on a decision. *Groupthink*, as per the literature definition, is the conformity of a social group imposed on its team members (Whyte Jr., 1952). In engineering teams with diverse hierarchical statuses, status disparity influences group decision-making, often favoring high-status members. In a situation under stress, team decisions congregate around high-status members due to their perceived competency (Salas, 1991). Such tendencies can have negative implications for technical decision-making, with high-status members disproportionately influencing the decision process.

Decision analysis is an objective analytical tool that can also be used to re-assess existing decisions based on new information or updated objectives and constraints. The result of content analysis (Theme 9) shows that the technical decision-makers would reconsider prior decisions in light of new information. However, if a project was nearing completion and ample resources had already been invested, they tend to escalate their commitment towards prior decisions, instead of looking for an optimal solution. The literature suggests that individuals with an *escalation of commitment bias* tend to reinforce their commitment to a decision when significantly invested in time or money, or will be perceived as responsible for potential failure (Staw, 1976). Schmidt and Calantone (2002) suggested that the bias may increase the likelihood of product development failures due to decision-maker's hesitancy to discontinue unsuccessful projects. Another possibility, *risk aversion* might also be at work in these situations. Theme 9 further noted that the possibility of project failures due to their inaction towards risks would compel them to re-consider their decision, even when they had heavily invested in the decision. This behavior aligns with prospect theory, which posits that risk-averse individuals tend to place more value on losses than equivalent gains (Kahneman & Tversky, 1979). Consequently, a decision-maker's risk tolerance and bias can significantly influence the success of engineering projects.

Based on the discussion above, this study found that technical decision-making in engineering organizations appears to be rife with social and cognitive biases; where the biases distort information processing, affect alternative selection, and influence decision revision. Heuristics and biases are deeply embedded in the human decision-making process. These biases can be favorable because rational analysis has limitations and knowledge of experienced decision-makers can augment the decision-making process to yield an optimum decision. Conversely, biases can negatively impact the technical decision-making process. Over-reliance on human intuitions may result in less effective decision-making because humans may bring in other factors such as emotions and personal background when making a decision.

RQ 1.4: To what extent do decision-makers exhibit rationality in technical decision-making?

The rational model of decision-making can be described as “a model where individuals use facts and information, analysis, and a step-by-step procedure to come to a decision” (Uzonwanne, 2016, pg.1) The rationality can be theoretically achieved assuming humans can express their preferences consistently (Von Neumann & Morgenstern, 1944). When human behavioral elements are factored into the decision-making equation, their biases interfere with the rationality of the process. However, It is important to emphasize that biases should not be seen as errors, but incapability to achieve certain abstract rules (Kahneman, 1991).

Exploratory data analysis (Section 5.2) indicates that decision-makers consistently relied on their biases to some extent when making technical decisions. Overall, with a mean of 2.56 on a scale of 1 to 4, decision-makers appeared moderately biased when making technical decisions (see Result 1). There exists a high expectation of rationality in technical decision-making (Theme 4, Section 5.2.1), especially in high-stake situations such as in safety-critical industries where objective-driven procedures were established for technical decisions (Theme 2). The mean score of 2.56 in this study highlights the discrepancy between expected rationality and the reality of the decision-making process, where decision-makers understood the importance of rationality yet remained moderately biased. The degree of biases also differed at different stages of the decision-making process.

Decision-makers displayed a moderate bias when processing information and making decisions but were slightly less biased when revising decisions (see Result 2). They often did not accept information at face value but used their social and cognitive biases to process information. This is probably because, in the age of pervasive fake news and misleading information, relying on intuitions to filter out erroneous information may seem to be more reliable. This was shown in the results of the qualitative analysis (Theme 6) where decision-makers questioned the accuracy of the information and source reliability. However, decision-makers tend to be more ‘rational’ when revising decisions at a later stage in the product development process. This was due to the availability of new information during decision revision and the need to assess project impacts objectively (Theme 9).

The majority of decision-makers did not make their final decisions based on recommendations from decision analysis tools (Result 3). This hesitation is rooted in concerns over the tools' reliability and the comprehensiveness of the information provided (Result 4). Decision analysis tools rely on users to collect and feed information into the tools, and thus, the quality and completeness of information are dependent on the user’s input. Since decision-makers processed information according to their personal judgments (T*heme 6*), the information fed into the analytical tool might have been disregarded or biased by the decision-makers. This calls into question the objectivity and robustness of the tool. Even though decision-makers value information completeness, their behaviors often contradict this belief, where *Result 5* showed that the participants only requested 57% of the available information. Interestingly, participants who doubted the information completeness of the decision analysis in Result 4 also requested, on average, merely 56% of the available information. Hence, it can be argued that participants relied on their own knowledge and experience, and therefore, would not have to depend on external information to make decisions. This is supported by the finding (R*esult 5*) where the experienced decision-makers requested only 49% of the available information, in comparison to 63.9%. with the less experienced participants.

Result 3 demonstrates a preference for team-based decision-making (62.8%) over individual decision-making (21.8%). This correlates with the qualitative finding (Theme 1) that validates the collaborative nature of technical decision-making. Decision-makers pursued inputs from team experts and prioritized consensus decision-making (Themes 3 & 4). This resonates with existing research suggesting the need for specialized, multifunctional teams in highly complex engineering projects (Chen & Lin, 2004)**.**

Furthermore, this study also identified a correlation between decision-makers' risk tolerance and bias tendencies. Result 8 indicates 73.4% of participants had low risk tolerance and Result 9 shows those with low tolerance relied heavily on biases. This result is not particularly surprising as a study by Mufti, Bakht, Tadros, Horosko, & Sparks (2005) showed that civil engineers are more conservative in their engineering judgments. Another study that systematically assessed risk attitudes among engineers suggests an inclination toward risk aversion over risk-seeking behavior (Van Bossuyt, Dong, Tumer, & Carvalho, 2013).

Hence, it can be summarized that technical decision-makers appear to be moderately biased when making technical decisions (Re*sult 1*), as they exhibited noticeable bias but were leaning towards impartiality. This can be attributed to their strong social bias (Re*sult 7*), reliance on team consensus (Re*sult 3*), and cautious approach to using decision analysis (Re*sult 4*). This can be due to the fact that decision analysis, as a tool for rational decision-making, possesses several shortcomings, such as it is highly dependent on the users, information that is fed into the tool might already be biased, and have a weak theoretical foundation (Austin-Breneman et al., 2016; Dowding & Thompson, 2009; Goel et al., 1992; Keeney, 1982). Furthermore, the knowledge and experience of subject matter experts within the decision-making groups were highly valuable to the team and were used to support making robust technical decisions (Them*e 1, Theme 3 & Theme 4*). However, the study shows that that decision-makers did not completely dismiss decision analysis tools but used the tools as a guide to make decisions. This is in line with the objective of decision analysis where the tool should assist decision-makers to make better decisions, and not make the decision itself (Wright & Goodwin, 2009). Therefore, the observation in this study that decision-makers utilized rational analysis and personal judgments in tandem (Theme *3*) might prove to be a good synergy to achieve better technical decisions.

5 Conclusion

In everyday practice, rational analysis is expected to be used as the governing principle for decision-making, where data are fed into the process to obtain rationally driven technical decisions. However, the outcome of the process may deviate from the outcome of the rational process due to the behavioral factors of human decision-makers. This research attempts to explain the dynamic interplay between rational and behavioral components in the technical decision-making process in product development. This chapter will address the main research question by weaving together the research findings from both qualitative and quantitative data to form an understanding of the technical decision-making process in engineering organizations. This chapter also outlines the contributions of the research and provides a roadmap for future research directions, suggesting areas that can be explored to further deepen the understanding of the subject matter.

RQ 1: How do engineering organizations make technical decisions during product development?

Technical decision-making in engineering organizations can be viewed from two perspectives: normative decision-making, where organizations prescribe guidelines for optimal decision-making, and descriptive decision-making, which describes how people within the organization behave when actually making decisions. Based on research findings and data analyses, normative decision-making centers around rational analysis and rule following while descriptive technical decision-making is a group effort where decision-makers do not strictly follow the decision-making guidelines prescribed by their organizations but instead rely on their heuristics which can be subjected to bias. In achieving effective decision-making, rational analysis is often intertwined with the biases of the decision-makers, such as confirmation bias and escalation of commitment.

Engineering organizations, especially in the safety-critical complex-system industries such as space, medical devices, and automotive, require the need for robust technical decision-making due to the inherent risk and complex nature of their products. This is reflected in the relevant international standards and industry-wide norms and guidelines where the importance of rationality and objectivity in decision-making is heavily emphasized (refer Section 2.5). At the same time, organizations also balance the risks and opportunities of rational decision-making with organizational constraints, such as cost, manpower, and time. However, it was observed that the decision-making in these organizations is governed by the rule-following method because it has to balance desired rationality and the required efficiency of the organizations (refer Section 2.4.3). In the rule-following method, organizations loosely prescribe a set of rationally-driven rules and guidelines to be followed, allowing some degree of flexibility for the decision-makers to navigate the complexity of the decision contexts (AIAG, 2008; VDA, 1998). This flexibility enables heuristics and biases to creep in and is reflected in the decision-maker's behavior in making technical decisions.

Decision-makers in engineering organizations employ all three methods of decision-making – rule-following, rational analysis, and personal judgment – to make technical decisions. The flexibility of the prescribed decision-making guidelines allows them to align decision management strategy with the project needs and risks involved. The decision-makers may use decision analysis tools to guide them during the decision-making process, but the results of the study reveal that they do not necessarily rely on the tools to make final decisions (Result 3). The decision-makers highly favor team consensus in decision-making, as they value the experience of the subject matter experts and readily trust information from ingroup sources (Result 3, Theme 3, Theme 4 & Theme 6). Social and cognitive biases thrive in the kind of environment where personal judgments exist. This is in line with the research findings where technical decision-makers have stronger social bias compared to cognitive bias resulting in a higher likelihood of bias to prevail in the technical decision-making process, especially in group settings (Result 7). Group decision-making is undoubtedly beneficial to achieve well-rounded decisions, but the effect of social biases may compromise optimal decision-making.

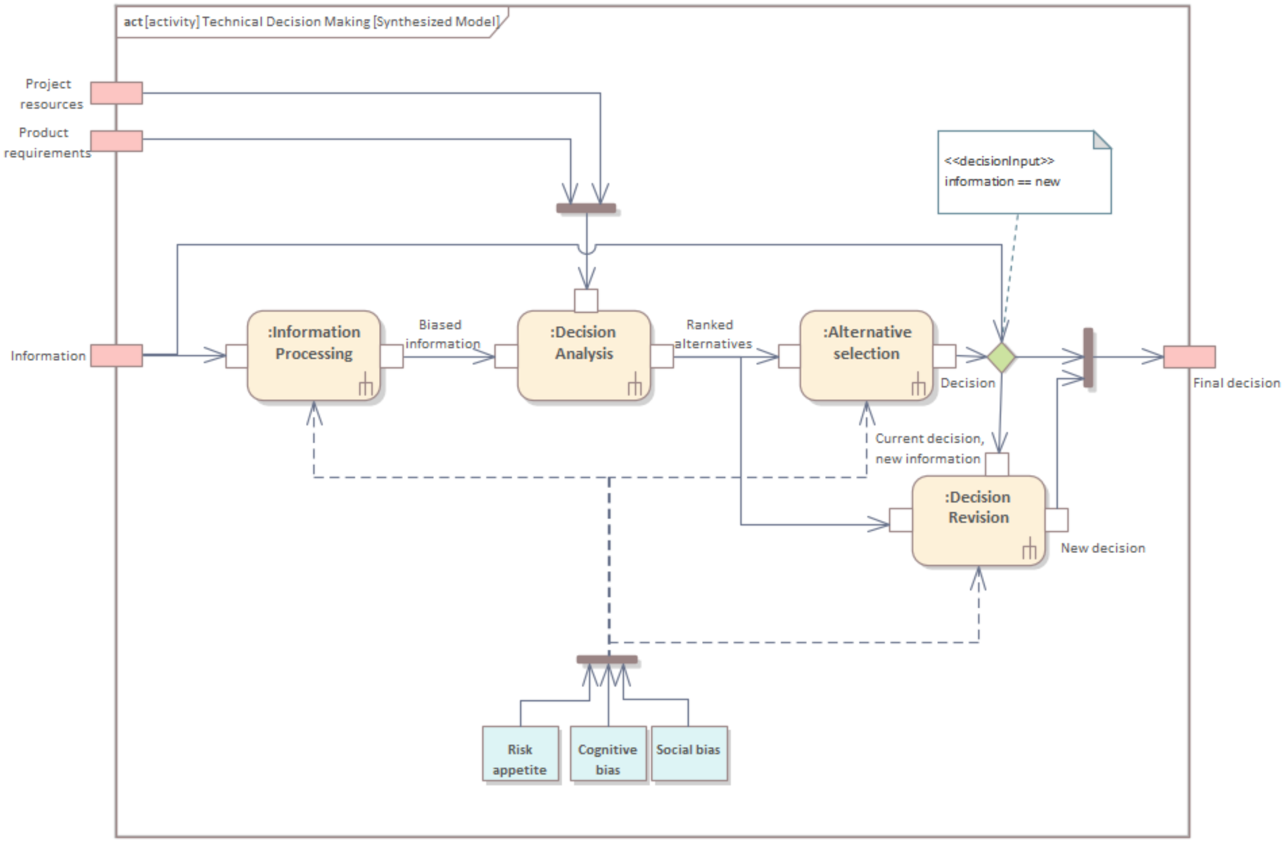

Figure 49: Synthesized Model of Technical Decision-Making in Product Development

Figure 49 summarizes a descriptive model of the technical decision-making process in product development as found and analyzed in this study (Section 4.1). Biases in the technical decision-making process can alter the input information and thus affect decision outcomes. Information is processed through the biased lens of decision-makers, where information that is not aligned with their knowledge may be filtered or discarded, and those they only deem reliable are accepted. If the information fed into the decision analysis tools is biased to begin with, then the outcome of the analytical process will also be inadvertently biased. For example, machine learning, as a decision analysis tool, has been found to be biased towards specific groups of people. This is mainly caused by the biased data with which the machine learning algorithms were trained (Mehrabi, Morstatter, Saxena, Lerman, & Galstyan, 2021). Concurrently, as found in the current study, participants have been observed to rely on their heuristics to challenge and to some extent discount the information that differs from their knowledge or their consensus (Theme 6). This is an indication that confirmation and in-group biases exist in the information-processing stage of the decision-making process (Figure 37).

The technical decision-making process is based on the rational model but can be influenced by the biases of the decision-makers. Even though decision-makers use decision analysis tools to guide their decision-making process, they do not rely on the decision analysis tool recommendation to make a decision (Result 3). In fact, alternative selection bias was observed in the study that may affect the outcome of the decision-making process (Result 2). Decision-makers also tend to trust their judgments and rely on the opinions of their group (Result 3). When under pressure, particularly during the final stage of a project, their decision revision bias would affect their decision where they would reaffirm their prior resolution to meet a pressing deadline (Result 2).

Decision-makers in engineering organizations seem to be moderately biased and risk-averse when making technical decisions. Participants' demographics, such as work experience and position, show no significant bias deviation between the decision-makers (Result 6). The mean difference between the bias tendency of engineers, project managers, and department managers, and early-career and late-career executives was not statistically significant. However, the study showed that their risk averseness had a significant effect on their bias tendency. 73.4% of the decision-makers had low-risk tolerance and participants with low-risk tolerance were found to have a stronger bias tendency than those with high-risk tolerance (Result 9). In an era increasingly affected by the proliferation of misinformation, it is crucial to meticulously scrutinize all information prior to making decisions, particularly when it pertains to safety-critical systems.

Therefore, this study can conclude that technical decision-making methods employed by engineering organizations, especially those in safety-critical industries with highly complex systems, do not completely embrace rationality in their decision-making process. The organizational need to strive for rationality and efficiency compels decision-makers to adopt rule-following approaches. However, at the same time, the flexibility of the prescribed decision-making guidelines allows decision-makers to maneuver the complexity of the technical decisions and make decisions as they see fit. This is because even though organizations must adhere to stringent safety standards, these standards do not explicitly define the decision-making methodologies or tools to be used (ECSS, 2017; IEC, 2020; ISO, 2011). This flexibility makes way for heuristics and biases to creep in. This is duly reflected in the way decision-makers actually behave to make decisions; they employ rule-following, rational analysis, and personal judgment concurrently. Simultaneously, social and cognitive biases influence the decision-making process where group decision-making is highly valued and plays a role in the process. This tendency for social biases causes decision-makers to rely on human intuitions instead of rational analysis. Human intuitions are highly subjective, and their reliability and effectiveness are dependent on the experience, knowledge, and emotional intelligence of the group members.

Finally, heuristics, which can be subjected to bias, do not necessarily lead to less effective decision-making. While decision analysis is widely regarded by many organizations as a valuable tool for making robust decisions, over-reliance on pure rationality in decision-making can lead to an overwhelming amount of analysis, diminishing the inclination to act (Hodgkinson & Starbuck, 2008). Human intuitions, on the other hand, can offset the dependence on rationality as the knowledge of experienced decision-makers can add value to the decision-making process. Although heuristics are often viewed as irrational, Robbins and Judge (2001) opine that heuristics do not always contradict but rather can complement rational analysis and they advocate for integration between rational analysis and heuristics to enhance decision-making processes. Furthermore, Kahneman (1974) posits that while some heuristics are "highly economical and usually effective," they can result in systematic errors; he, therefore recommends a deeper understanding of heuristics and biases to enhance decision-making under uncertainty.

In conclusion, the technical decision-making process in industries involving safety-critical, highly complex systems is a rational act influenced by behavioral elements. Despite stringent safety standards and regulations, the technical decision-making process in these engineering organizations is not rigidly controlled. This can be attributed to the inherent limitations of decision analysis. While numerous scholars recommend the cautious integration of heuristics into the technical decision-making process, INCOSE advises a careful approach when using decision analysis due to its various limitations. Therefore, the researcher believes that rational analysis is a powerful tool that should be pursued but at the same time, behavioral elements be allowed to co-exist in the decision-making process. As long as engineering organizations can identify and manage the negative side effects of heuristics and biases in the decision-making process.

5.1 Contributions

This research provided readers with valuable insights into the expected and actual technical decision-making process in engineering organizations in the study. The study analyzes the technical decision-making process in product development of engineering organizations across multiple industries. Four key contributions of the thesis are outlined as follows:

Contribution #1: Synthesized Model of Rational and Behavioral Technical Decision-Making in Product Development

The thesis proposes a synthesized model of rational and behavioral technical decision-making, specifically applicable to product development. The model was developed by integrating the conceptual framework with a decision context (i.e.: product development). Qualitative research facilitated the identification of human factors, namely social bias, cognitive bias, and risk appetite, affecting technical decision-making, which were then incorporated into the model. The model outlines three decision-making stages that can be influenced by human factors – information processing, alternative selection, and decision revision. The human factors identified through the research are cognitive and social biases and risk tolerance. This theoretical contribution enhances the understanding of how biases may impact decision analysis and provides a comprehensive framework for studying the technical decision-making process.

The study of bias influence on the decision-making process within a product development context is sparse. Most studies that explored the existence of heuristics and biases in the technical decision-making process, focus on the influence of a specific bias only on the outcome of the process (Hallihan, Cheong & Shu, 2012; Zheng, Ritter & Miller, 2018; Nelius et al., 2020; Agyemang, Andreae & Mccomb, 2023). This thesis, on the other hand, holistically modeled the dynamic interplay between rational and behavioral elements of human factors in the technical decision-making process.

Contribution #2: Insight into technical decision-making methods employed in engineering organizations

The thesis provides valuable insights into the decision-making process employed in engineering organizations for technical decisions. It lays out the current landscape of the technical decision-making process in engineering organizations, especially those in safety-critical industries, and analyzes the gaps and deviations between the expectation and reality of the decision-making process. It further highlights the importance of understanding the impact of human behaviors and their role in governing technical decision-making. This practical contribution aids organizations in understanding and evaluating their decision-making strategies and processes, enabling them to make informed improvements. For example, the negative effects of information bias can be mitigated by establishing multiple redundant paths for processing information, which serve as checks and balances.

Current research on the decision-making process in product development often appears to overlook the current practices prevalent in industry. Many of these studies opted for secondary sources from academic papers instead of literature derived directly from industry sources (Tang et al, 2022; Nemtinov et al, 2019, Kranabitl et al, 2021). Moreover, some research relied on engineering students to examine the impact of bias on the technical decision-making process in product development (Hallihan & Shu, 2013; Gweon et al., 2015), raising concerns about the students' lack of real-world product development experience and expertise. In contrast, this thesis exclusively involves participants from various industries and directly references engineering organizations and industry documents as primary sources. Thus, it serves to bridge the theoretical insights of academia with the practical experiences of industry.

5.2 Limitations

As discussed in Chapter 2, a decision-making process is highly contextual. So, this thesis focused on the technical decision-making aspect of product development process in engineering organizations within safety-critical highly complex system industries. For that, a general model of the design development phase in product development, based on industry-wide applications, was formulated. Therefore, the model produced in this thesis may only be applied in the context of product development of safety-critical highly complex systems in engineering organizations. Its application in other decision contexts may need to be adapted accordingly.

Secondly, the Synthesized Model of Rational and Behavioral Technical Decision-Making in Product Development (Figure 49), may not account for all variables and factors influencing technical decision-making in safety-critical, highly-complex systems. The dynamic nature of decision-making processes coupled with unpredictable external elements, such as organizational, social, and political issues, contribute to unforeseeable factors that can affect the decision-making processes in ways not covered in this study.

Lastly, relying on qualitative methodology, such as interviews, may introduce subjective biases into the study. Data gathering via interviews enables exploration of the decision-making behavior in engineering organizations, however, the interpretations of the data were subjected to the researcher's knowledge of the subject matter, which might not capture the full spectrum of decision-making complexities in these environments. Additionally, the qualitative research sample size was limited to 15 participants, as data saturation was achieved at this point. However, it's important to note that if more interviews had been conducted, additional information might have emerged but would have been infrequent.

5.3 Future Direction

This research has shed light on the intricate interplay between rational and behavioral elements in technical decision-making within engineering organizations. There are several promising avenues for future exploration of this topic. These potential directions can further enhance our understanding of decision-making dynamics, contribute to more effective decision processes in engineering organizations, and ultimately the body of knowledge on decision-making:

Academia, Future Direction #1: Advanced modeling technique

Employing advanced computational modeling techniques, such as Partial Least Squares Structural Equation Modelling (PLS-SEM), could provide a more comprehensive understanding of how behavioral elements manifest in decision-making processes and possibly forecast decision outcomes using a trained model.

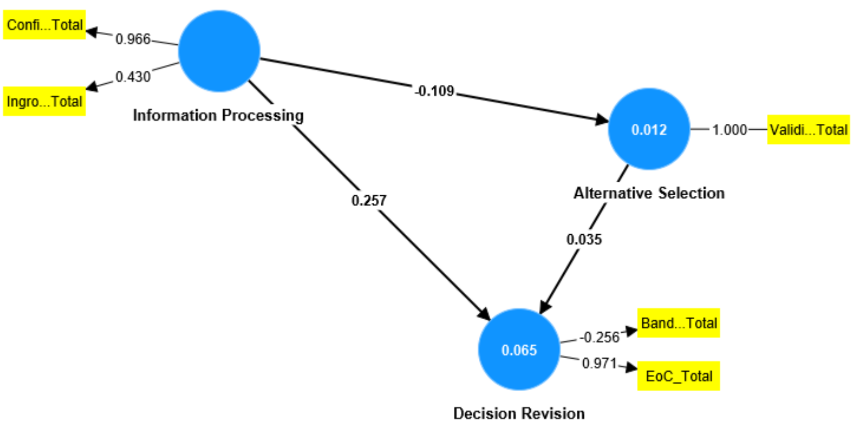

Figure 50: PLS-SEM causal model

PLS-SEM enables researchers to model and test causal relationships between variables, as it estimates model relationships through an iterative sequence of ordinary least squares regressions (Hair et al., 2016). The first-generation multivariate data analysis techniques (e.g.: regression and analysis of variance) are limited in capabilities, such as analysis of basic model structures and observable variables (Haenlein & Kaplan, 2010). PLS-SEM, on the other hand, could be used to delve deeper into understanding the intricate mechanisms in technical decision-making, especially to discover if latent variables, such as behavioral elements, may cause deviations to rational decision-making. To illustrate this, a structural model depicting hypothesized relationships between latent variables could be constructed to understand causality between bias clusters (Figure 50). Structural model path coefficient, which is a value between -1 and +1, denotes the strength of relationship or causality between the variables. For example, in Figure 50, the path coefficient of 0.257 shows fairly strong causality between *Information Processing* and *Decision Revision* latent variable. The significance of the relationship could then be measured using the p-value.

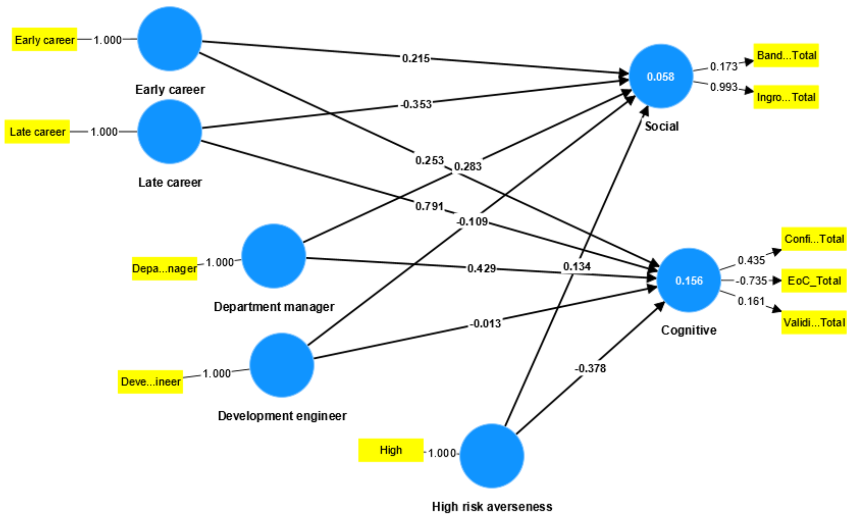

Figure 51: PLS-SEM predictive model

The predictive power of PLS-SEM could also be harnessed by developing a predictive model that could forecast decision outcomes. In order to do this, the models would have to be trained using a large number of datasets to ensure high predictive power and predictive relevance. These predictive models could guide decision-makers by offering insights into potential outcomes under different decision scenarios and demographics. For example, a structural model with hypothesized relationships between latent (e.g.: social and cognitive biases) and measured (e.g.: demographic parameters) variables could be constructed to predict the social and cognitive bias tendency of decision-makers based on their demographic parameters (Figure 51).

Academia, Future Direction #2: Application to different decision contexts

A natural progression for extending the findings of this research would be to apply the conceptual framework to various decision contexts within engineering organizations, outside of safety-critical highly complex systems industries. By examining the interplay between rational and behavioral elements manifesting themselves in different scenarios, a better understanding of decision-making dynamics can be accomplished.

In the thesis, the conceptual framework was applied to the product development decision context. This same framework could be applied to manufacturing, supply chain, and technical customer acquisition decision scenarios too. The findings of each application could show the nuances of human behavior in different technical decision-making contexts.

Industry, Future Direction #3: Human-oriented technical decision-making

Building upon the understanding that behavioral factors have an influence on the technical decision-making process, future research could look into improving the process in engineering organizations by integrating human factors into the process and ensuring optimal decision-making team composition.

The effectiveness of engineering organizations' technical decision-making should be evaluated in relation to the decision-making processes. As illustrated in Figure 49, it is important to safeguard the information input into the decision-making process from information-processing biases. This can be achieved by having subject matter experts objectively evaluate all information and critically assess the information sources. The objectives and constraints of technical decision-making processes must be also considered objectively in the process, without the influence of the decision-maker's judgment. While the use of decision analysis tools is highly recommended, it is important for engineering organizations to recognize that these tools are not infallible; thus, the outputs of these tools must be pragmatically yet objectively considered. To minimize alternative selection bias, any deviations from the tool's recommendations should undergo review by the stakeholders and be based on technical analysis.

As explained in Section 4.3, technical decision-making is a group effort, underscoring the importance of the composition of the technical decision-making team in yielding optimal decisions. At a minimum, the team should be composed of relevant stakeholders, subject matter experts, and support members. In a team setting, social biases can affect the technical decision-making process. Factors such as group cohesion, diversity, status, culture, and established norms can have impacts on group productivity and the quality of decisions made (Forsyth, 1990; Robbins & Judge, 2001; Berger, 1977; Janis, 1971). Therefore, engineering organizations must give careful consideration to these variables when assembling a technical decision-making team.

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7 Appendix

Appendix A: Participant Information Sheet

Participant Information Sheet - **Modeling of Organizational decision-making processes With Consideration of Human Factors**

This interview is conducted as a part of a PhD project. Through the interview, we aim to develop a better understanding of organizational decision-making processes used in the industries specifically for product development technical decisions.

This project looks to gather qualitative data from semi-structured depth interviews and quantitative from questionnaires. From these we aim to develop an in-depth understanding of the decision-making processes used in product development lifecycle in the industries, exploring in particular: i) Industry-specific decision-making processes, guidelines and best practices, ii) the descriptive decision-making process in the industry and iii) the influence of human factors in normative organizational decision-making processes.

You have been chosen to participate in your positive response to the interview. You can withdraw at any time without giving a reason. Interviews will take around 1 hour at a pre-decided location. Your contribution to the research will form part of the final report of the PhD thesis. Subject to your consent, there will be an audio recording of your responses during this research for analysis purposes. These recordings will not be utilized for any other purpose without your express written consent and access to the original recordings will be restricted. You will not be able to be identified in any ensuing reports or publications and we confirm that the interview will be on the condition of anonymity for the interviewee.

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Signature	Date	Print Name
____________________	________________	____________________

Appendix B: Interview Guide

Objectives

The objectives of this qualitative research are:

- to verify the unified model of rational and behavioral technical decision-making
- to understand actual decision-making process in engineering organizations
- to uncover new information that can be used to improve the model
- to detect biases that exist during the technical decision-making process

Protocols

- Provide respondent with participant information sheet
- Inform respondent that they can withdraw from the interview at any time
- Inform respondent that they do not have to close any confidential organizational information or personal information
- Inform respondent that they are being recorded but their names and personal details will not be stored or disclosed
- The questioning does not to follow the specific ordering, but adapted according to the flow of the conversation

Initial Questions

1. **What kind of technical decisions do you make on a daily basis?**
   Note: Ask for examples of the technical decisions

2. **Does your organization prescribe technical decision-making methodologies or guidelines?**
   Objective: to understand the organization's decision-making procedures
   Note: Follow up by asking about specific tools or methodologies used in the organization

3. **How do you, personally, make technical decisions?**
   Objective: to understand personal tendencies in making decisions

Main Questions

4. **How do you decide if a decision has to be made using an analytical process or personal judgment?**
   Objective: to probe if decision analysis is being used in all decision scenarios
   Note: Probe the scenarios where this strategy is applicable

5. **If an analytical process is applied to help decision-making, how do you choose between the alternatives?**
   Objective: to investigate alternative-selection bias

6. **How do you evaluate the information that is provided to make specific technical decisions?**
   Objective: to investigate information-processing bias

7. **If a decision has been made and new information is provided afterward, what do you do?**
   Objective: to investigate decision-revision bias

8. **What is your approach to routine decision-making with slightly different information?**
   Objective: to probe if there are any other bias categories

Appendix C: Content Analysis: Full

Questions	Part.	Condensed Meaning Unit	Codes	Theme
1. What kind of technical decisions do you make on daily basis?	A	Decides mostly on organizational matters in project meetings	engineering management decision	
	A	Defines and decides measures to facilitate project work	engineering management decision	
	B	Selection of designs and solutions exist in the organization, decision-maker chooses the most suitable ones for the situation	product design decision	
	B	Decisions are normally made or facilitated by the team	group decision-making	1
	B	Decision is made from personal judgment based on expert inputs	personal judgment based on expert inputs	6
	B	designs and solutions available from the organization may not totally fit with customer requirements	product design decision	
	C	Decisions on system design for platform and production locations	product design decision	
	D	High level guidelines are provided on how to make decisions, but they are open to interpretation	DM procedures are not always detailed	3
	E	Manufacturing decisions in production machine maintenance	manufacturing decision	
	F	Technical project management. Cost, timing, technical decisions.	technical project management	
	F	Information is gathered within the team.	group information processing	1
	F	Decision is made in consensus through brainstorming.	team consensus	1
	G	Technical decisions to release supplier components. Requirement-based technical decision	supplier-based design decision	6
	H	Integrating systems between various directorates	systems integration	
	H	Early phase of development, making high level, key technical decisions	high level design decision: early phase	
	H	Later stage, making technical decisions that are more geared towards technical problem solving and if deviations can be accepted	low level design decision: later stage	
	H	Development is an iterative process. Concepts are checked with in-depth design to check their feasibility already in the conceptual stage.	requirement-design iterative decisions	
	I	Software engineer oversees sub-contractors	supplier-based design decision	
	I	Decisions are made in progress meetings and design reviews	group decision-making	1
	I	IF the decision is simple and has not much impact on the project, the discussion will be short and straightforward	PJ = Simple and easy decision	7
	J	Early phase studies, looking at new topics and problems, their solutions and the pros and cons	high level design decision: early phase	
	J	Study requirements and concepts from various directorates, and help them make decisions and assess feasibility	system analysis	6

	K	Project management is a kind of decision-making, only on high level non/technical decision. Sometimes, make the final decision	Project management	
	L	Handle production targets and issues	manufacturing decision	
	M	Most of technical decisions are about requirement negotiations, and the politics involved. Technical part is the easy bit.	technical decision is negotiation	1
	M	Decision-making in space sector tends to be more conservative		
	M	Technical decisions are political. You don't make optimal decision it first time around, so it can be optimized at later stage.	technical decision is political	1
	N	Technical decision is about balancing needs of stakeholders	technical decision is negotiation	1
	O	Technical decision has to be backed by rationale. In term of assessment and documentation.	technical decision must be documented and rationalized	6
	O	The decision taken also has to be verified through analytical methods or tests.	Technical analysis is needed	6
2. Does your organization prescribe technical decision-making methodologies or guidelines	A	BES, process-driven problem management tool for technical issues	DM procedures are available	3
	B	Organization prescribes DM guidelines	DM procedures are available	3
	B	Technical change, either production or development issues, is made within a team through change control board	DM procedures are available	3
	B	DRBFM and focus matrix to identify criticality of decision and its impact on other processes	analytical process tools	3
	B	Decision rules are available for making change decisions	DM procedures are available	3
	B	Decisions are made by a team	group decision-making	1
	B	Decision rules also prescribe the methods to evaluate the criticality of decision	DM procedures are available	3
	C	There is process on structuring and documenting decisions	DM procedures are available	3
	C	Basic guidelines on joint working between organizations on product development	DM procedures are available	3
	C	Bosch Engineering System procedures describes methods to develop and evaluate concepts. E.g.: using cause & effect relationship method, focus analysis and decision matrix	analytical process tools	3
	D	There are standardized routes to approve business or technical decisions	DM procedures are available	3
	D	On smaller or less important decisions, no guidelines are specified. Big and important decisions will rely on official DM guidelines	DM procedures are available	3
	E	There is no decision-making guidelines by company	No guidelines or tools	3
	F	No company guidelines on DMP. Team comes up with relevant DM methodologies.	No guidelines or tools	3
	G	DM guidelines, i.e.: checklist, is prescribed by company.	DM procedures are available	3
	G	Checklist is very important. But not all points are top priority. Prioritization is based on experience.	DM procedures are not always followed	11

	H	Yes, based on organization’s systems engineering handbook	DM procedures are available	3
	H	Guidelines are rarely used because it’s far away from reality	DM procedures are not always followed	11
	I	Specific guidelines to procure software is not available.	DM procedures not detailed	3
	I	But steps to general procurement is available and strictly defined, based around review process (critical design review) at milestones	DM procedures are available	3
	I	Design review is based on objectives, defined in ESA standards	DM procedures are available	3
	I	Design review process is not detailed in the guidelines. Different departments do it differently based around the guidelines	DM procedures not detailed	3
	I	Department’s review process is not documented but more on the way of working set upon by the higher management.	DM procedures not detailed	3
	J	Established steps are provided to forward the projects, and this must be followed to reduce project risk	DM procedures are available	3
	J	Yes, organization has guidelines and use international standards: Concept selection guidelines is provided.	DM procedures are available	3
	K	Organization prescribes strategic methodology to make technical decisions. Normally in terms of development reviews	DM procedures are available	3
	K	Reviews and decisions are done in groups. Even failure analysis and its sequent decision is done through review	group decision-making	1
	K	Processes are dictated by the industry group standards. Organizations can tailor it.	International standard procedures are followed	3
	L	No specific DM methodologies are prescribed. However, general methodologies and tools are provided	DM procedures not detailed	3
	M	No detailed guidelines are prescribed by the organization. Each department has to create their own.	DM procedures not always available	3
	M	DM guidelines are not properly documented but passed down verbally.	DM procedures not always available	3
	M	The guidelines are broad in general, but can be very specific in some critical areas	DM procedures level of detail is inconsistent	3
	M	Certain guidelines drill down to minute details of work	DM procedures level of detail is inconsistent	3
	M	Some guidelines became requirement as in, it has to be done in the exact way	Guidelines can become requirements	
	M	In general, the guidelines have to stay as broad as possible, because design process requires as less constraint as possible to stay innovative	DM procedures not always available or detailed	3
	N	In medical device industry, what important is the documentation of design process.	technical decision must be documented and rationalized	6
	N	No prescribed methodology. Usage of specific tools are not mandatory.	No guidelines or tools	3

	N	In the industry, high level guidelines are provided instead of specific tools	DM procedures not detailed	3
	O	No specific guidelines are prescribed.	No guidelines	3
	O	Certain tools, such as traceability matrix, FMEA, simulations etc., are used to backed technical decision.	analytical process tools	3
3. How do you, personally, make technical decisions?	A	Try to understand factors to make decisions, through gathering feedback from many people	Data gathering from experts	6
	A	Asks technical judgment from several trusted competent people	Reliability of information seeker	2
	B	DMP is hard to fulfill. Limitation of resources and slow decision process are caused by considerable preparation work.	analytical process is resource-heavy	12
	B	DMP method is chosen, through expert judgments, based on its cost-benefit ratio	analytical process is based on weighted criteria	4
	B	Pre-judgment is made based on heuristics to hasten decision process and get a buy-in	PJ = quick	7
	B	Full DMP method is not followed	analytical process is not used fully	4
	C	Personal preference is using rational analysis, by systematically understanding the problem and use DRBFM	analytical process is preferred	4
	C	Engage the team to make decision	group decision-making	1
	D	Any changes must go through impact analysis to check if the decision will impact technically or commercially	analytical process is preferred	4
	E	Group decision-making. Teams give inputs, he makes decision	group decision-making	1
	E	Analytical process is used throughout the decision-making process	analytical process is preferred	4
	E	It is important to use analytical process, to justify decision	analytical process is preferred	4
	F	Personal DMP is using analytical approach, decision matrix.	analytical process is preferred	4
	G	Checklist is the main source of DMP, but personal experience, based on intuition, is also used.	DM procedures are not always followed	11
	H	Systematically ruling out options based on personal judgment. If the leftover options are unclear to choose, cognitive trade-off table is being used.	Analytical + personal judgment: cognitive trade-off	4
	H	Trade-off criteria are based on technical, financial and time aspects: If no best solution can be found, the next best one is chosen	cognitive trade-off is based on weighted criteria	10
	I	Technical decisions, with suppliers, are normally made without involvement of management if agreement can be reached	management involvement for critical decision	13
	I	Technical decisions are evidence-based, e.g.: analysis, test, expert judgment, in the organization	technical decision is based on evidence	6
	I	DMP process is multi-layered and horizontal, involving many people and a lot of time. One decision affect another.	group information processing	1

	J	Concept is selected based on weighted criteria within the same boundary. Weightage has to be decided within the project. conditions	analytical process is based on weighted criteria	10
	J	Trade-offs are sometime conducted qualitatively	Analytical process can be subjective	4
	J	Analytical approach is sometimes not done, because not enough information or not necessary	analytical process is information-heavy	12
	J	Board decides within project cycle to proceed with the next phase based on the information provided to them	Decision checkpoints are managed by management	13
	J	In daily technical decisions, decision is taken based on expert judgment from specialists	expert opinions are needed during decision making	6
	K	Personally, based on experience. But experienced engineers normally make decision based on experience.	Personal judgment is preferred	4
	L	Personally, DM is based on analytical process through root cause analysis and problem solving	analytical process is preferred	4
	L	Root cause analysis is done as a team	group decision-making	1
	M	Most decisions came unconsciously through innate knowledge and experience	Personal judgment is the natural way of DM	4
	M	The decisions later must be justified through conscious decision-making.	technical decision must be documented and rationalized	6
	M	If previous decisions do not fit with current set of requirements, analytical DMP needs to be done	Previous decision is revalidated	8
	M	Decision-making is a longitudinal process. It is a series of DMP that accumulates over time.	Decision affects one another	
	M	DM is a team effort, that also involves external teams	group decision-making	1
	N	Based on personal judgment and experience, after considering all of the inputs.	personal judgment based on expert inputs	4
	N	DMP is intuitive and to be rationalized to the audience.	technical decision must be documented and rationalized	6
	O	Personal preference is to back technical decision with sufficient rationale.	technical decision must be documented and rationalized	6
	O	Prototyping, simulation calculation, statistical and analytical approaches are used to rationalize the decision	Technical analysis is needed	6

4. How do you decide if a decision has to be made using analytical process or personal judgment?	A	Decides to choose between analytical process and personal judgment based on complexity of the topic but mostly using gut feeling.	PJ = Simple decision	7
	A	Also depends on the completeness of information, the stake of the decision and time constraint	PJ = time constraint, Incomplete information	7
	A	Views strategic nature of the decision as a very important factor	PJ = low risk	7
	A	Evaluates the completeness of information, as humanely feasible, to be sure of decision	Completeness of information	2
	B	Decision to use DMP or heuristics from experience, based on the risk of the situation. If the risk is high, use DMP; if low, use heuristics	PJ = low risk	7
	C	Technical decisions are always combination of analytical and personal judgment	both analytical and personal judgment is used	4
	C	The expert views are highly valued even though analytical process shows otherwise	expert opinions are needed during decision-making	6
	D	The decision-maker has to evaluate personal judgment vs analytical process on case-to-case basis.	both analytical and personal judgment is used	4
	D	Personal judgment, depending on the decision-maker experience, can help to understand the bigger picture for better DM	PJ = bigger picture	7
	D	Long term planning is better reserved for personal judgment because there are too many variables and expert's knowledge and experience help	PJ = long term planning	7
	E	Analytical process is preferred over personal judgment; it is the right thing to do and can be used as justification	analytical process is preferred	4
	E	Analytical process is used concurrent with team discussion	team consensus	1
	F	Risky decision will be made using analytical approach.	AP = risky decision	7
	F	Low risk normally requires fast decisions. Decision shall be made via experience.	PJ = time constraint, low risk	7
	G	Analytical vs Personal approaches depends on the topic. Straightforward and easy decisions can be made personally.	PJ = low risk	7
	G	For critical decisions, guidelines are method of preferences.	AP = critical	7
	H	Personal judgment is subjective. Analytical approach, i.e.: performance analysis, has to be performed for good decision-making.	Analytical approach is preferred	4
	H	Limited time, manpower; expertise and information hinder analytical approaches	PJ = time constraint, Incomplete information	7
	H	Relying on proper analytical approach is difficult, personal judgment can be done, but has to be careful	Analytical approach is preferred	4
	H	Personal judgment based on expert opinions are critical when limited information is available	expert opinions are needed during decision making	6

	I	Information is collected as much as possible, e.g.: technical analysis	Collect a lot of information	12
	I	Decision is made consensually with experts, based on personal judgment and data collected	group decision-making	1
	I		expert opinions are needed during decision making	6
	I	If a test fails, evidence must be collected and the DMP process is very long, based on technical discussions and justifications and costs	technical decision is based on evidence	6
	J	Criteria prioritization is done based on requirements, e.g.: cost, risk and schedule	weighted criteria are cost, risk and schedule	10
	J	Balance is based on project requirements. Technology is chosen if it fits with requirements, cost and risk associated with it	weighted criteria are cost, risk and schedule	10
	J	The risks are technical, schedule and technology	weighted criteria risk: technical, schedule and technology	10
	J	If the selected option risk is high, after all consideration, management has to make selection decision or which objectives are more important	management is needed if risk is too high	13
	J	More information is needed, and unknowns are to be reduced to increase DM confidence	Collect a lot of information	12
	J	All decisions must be based on technical feasibility: Personal judgment is also used	technical decision is based on technical feasibility	6
	J	The DMP is to systematically establish risks	Analytical approach is preferred	4
	J	It must be based on standards and feasibility study, using design analysis and peer review	technical decision is based on technical feasibility	6
	J	Confidence in DM can only be met with analysis based on professional experience	Technical analysis is needed	6
	K	Personally, follow the defined process, if the process doesn’t specify relevant decision-making method, then use personal judgment	Analytical approach is preferred	4
	K	Personal judgment and process outputs must align in order to justify decision	Personal judgment must be justified	6
	L	Personal judgment is discouraged. Data and facts are needed especially with technical decisions	Analytical approach is preferred	4
	M	All decisions need to be reviewed and justified in a team.	group decision-making	1
	M	Analytical process may be used to justify a decision.	technical decision must be rationalized	6
	N	The decision-making process is a team effort.	group decision-making	1
	N	Some inputs into DMP are not properly documented or have direct sources, they are based on knowledge of the organization and its preferences.	Some DMP inputs are based on organization's knowledge	

	N	Technical decision is also based on fulfilment of requirements.	Technical analysis is needed	6
	N	If it is a simple decision that can be taken by a single person, analytical tool is not needed.	PJ = Simple decision	7
	N	Simple design alternatives may not need elaborate criteria and scoring sheet.	PJ = Simple decision	7
	N	It is a complex decision, ranking process and elaborate analytical tool is needed. It also requires big team to decide on it.	AP = Complex decision, team effort	7
	O	Personal judgment should be limited to low impact decision scenarios.	PJ = low risk	7
	O	Analytical approach is optional for low impact decision scenario	AP = optional for low risk	7
	O	Any decision that can cause safety or functional issues must be backed by analytical approach	AP = high risk	7
5. If analytical process is applied to help decision-making, how do you choose between the alternatives?	A	Applies expert judgment, with the team, when evaluating alternatives	alternatives are discussed within team	1
	A	Evaluates if the alternatives fit with gut feeling	outputs fit with personal experience	9
	A	Questions the correctness of analytical process application if the outcome is not tallied with personal judgment	reliability of AP	9
	B	DMP method outputs may not be chosen because of the quality of the method itself.	reliability of AP	9
	B	Good DMP method quality: 1. rationale behind ranking	reliability of AP	9
	B	2. Holisticity of analysis	reliability of AP	9
	B	3. A lot of inputs	based on completeness of information	9
	B	Method outputs are only followed if rationale behind decisions is given, and the outputs are aligned with engineering experience	outputs fit with personal experience	9
	B	The DMP outputs are further “judged” based on: 1.the risk of the situation	risk of situation	10
	B	2. importance of the decision on organization’s strategies 3. the organization’s outlook	organization strategies	10
	B	4. Capability of the organization to execute the decision	organization resources	10
	C	Analytical process suggestions are taken into consideration, but final say is based on discussion with experts	expert opinions are needed during decision making	6
	C	If analytical process output doesn’t tally with experience, it is hard to accept its judgment	outputs fit with personal experience	9
	D	Proposed solutions from analytical tool will be used if the information fed is sufficient quantity and quality wise.	based on completeness of information	9
	E	The analytical process outcomes are not necessarily being followed. It depends on the decision context and environment	output fits with decision context and environment	10
	F	Ranked alternatives are first discussed within the team to get feedback from the analytical process.	alternatives are discussed within team	1

	F	The analytical process outputs are chosen, based on consensus of the team, because the process is trusted	alternatives are discussed within team	1
	G	The final decision is made using personal judgment, even though guidelines say otherwise. Afterwards, make proposal to change the guidelines	outputs fit with personal experience	9
	H	Driving performance parameters dictate the solution from analytical DMP, it is considered in the ranking	based on driving performance parameters	10
	H	The ranked alternatives are normally obvious from personal point of view	outputs fit with personal experience	9
	H	Analytical process outputs are not being considered because people already have their preferences	outputs fit with personal experience	9
	H	Proper trade-off table has never to be made when there's no clear option, because there's always, in the end, clear winner.	ranked alternatives is obvious from personal point of view	9
	I	DMP is mostly on finding the balance between cost and requirements based on a lot of evidence; supplier has to convince ESA using arguments	outputs are checked against cost and requirements	10
	J	Options are chosen based on constraints from higher management	outputs are checked against constraints by management	10
	J	The options are reconsidered again based on requirements, mostly the cheapest option that fits requirements	outputs are checked against cost and requirements	10
	J	It's also based on the feasibility of such option, especially timing	outputs are checked against timing	10
	K	Choose the proposed solution by analytical process. Risk analysis is part of the process.	analytical process is preferred	4
	K	Although the proposed solution is generally logical and technically better, it may cover all basis. Other factors, such as logistics and resources, must also be taken into account	based on completeness of information	9
	L	Follow analytical process proposed solutions.	analytical process is preferred	4
	L	Inputs to a DMP are gathered by a cross functional team. Solutions are also done together as a team	group information processing	1
	L	Proposed solutions by analytical process may not be followed fully, it also depends on the capability of the team to execute the solutions	based on team's capability to execute the alternatives	10
	L	Methodology is to guide, not to make final decisions	analytical process is just a guide	9
	M	The analytical process output is re-evaluated again based on other factors, including availability, and regulation. Technical consideration is not the only factor.	based on regulatory requirements, and availability of solutions	10
	N	DM, which has several alternatives, must be evaluated based on agreed criteria, with the team. The scoring is also done within the team.	group decision-making	1

	N	In principle, the first ranked proposal is used. However, personal judgment can also be used to re-evaluate the outcomes.	analytical process is preferred	4
	N	Analytical process is not truly objective. Based on participant preferences, they would strategically alter the weightage to influence the outcomes.	analytical process is not objective	9
	N	Analytical process shouldn't be the ultimate tool. Human must still be able to make the final decision	analytical process is just a guide	9
	N	Decision-makers in a DM group are not equal. Some members have greater power, which can override the team decision.	Team members have different decision-making power	
	O	The selection criteria of an analytical approach are important to decide if proposed solutions are valid. The selection criteria have to be based on certain guidelines.	selection criteria have to be standardized	
	O	The proposed solutions are also discussed with stakeholders and subject matter experts before being decided.	group decision-making	1
	O	The proposed solutions are also reviewed based on product requirements and cost factors.	outputs are checked again requirements and cost	10
7. How do you evaluate the information that is provided to make specific technical decision?	A	Prefers to make decision in a team, where everybody can voice out their opinions	group decision-making	1
	A	Generates consensus decision	**group decision-making**	1
	A	Checks the plausibility of information using experience	quality of information	2
	A	Accepts information if it fits with personal knowledge	**quality of information**	2
	A	Gathers more information if the information is not tallied to personal knowledge	Completeness of information	2
	A	Accepts the information more easily from trusted information sources	**Reliability of information seeker**	2
	B	The quality of information is not questioned. But the completeness of information is	Completeness of information	2
	B	The quality of how the information is being derived is checked.	quality of information	2
	B	The DMP tool data input process is not being used properly	analytical process is not used fully	4
	B	So, how the information is being presented and who are presenting the information is being personally judged	Reliability of information seeker	2
	B	If the correct experts are bringing the information, then the information details are trusted.	Reliability of information seeker	2
	B	So, how the information is being presented and who are presenting the information is being personally judged	Reliability of information seeker	2
	C	Information is filtered every time	Information is filtered	2
	C	The incoming information is reviewed with experts	group information processing	1
	C	The review is done in a group, and discussed individually before hand	group information processing	1
	D	All information will be evaluated based on the completeness of the information. Information is multi-layered.	Completeness of information	2

	D	Analytical tool requires as much information as possible to provide valuable outputs	Completeness of information	2
	D	Inputs should not be manipulated. All hard data information will not be filtered	All information is deemed correct	2
	D	All soft data, expert inputs, are evaluated based on the experience of the information compiler	Reliability of information seeker	2
	D	The inputs, hard and soft data, will be used to rationalize proposed solution from the analytical process	Information is filtered	2
	E	Historical data is used as is. But people’s experience is also considered as inputs	Completeness of information	2
	F	The inputs from domain experts and within the team are trusted because they are the experts.	Reliability of information source	2
	G	DMP inputs are evaluated personally based on the benefit of the project, technically, and company, financially.	based on project requirements and company's needs	2
	G	The inputs are evaluated based on their sources and compared against personal experience	Reliability of information source	2
	H	Input information has to be validated and evaluated before DMP	All information has to be validated	2
	H	The information is validated based on personal experience, regardless of the sources	All information has to be validated	2
	H	If all of the information cannot be validated due to time, only the odd ones are validated based on experience	AP requires time constraint, incomplete information, lack manpower	12
	I	Information is not validated because the sources are trusted if it comes from in-house specialist.	Reliability of information source	2
	I	If the information comes externally, they are being validated by the specialists	Reliability of information source	2
	I	Not all external sources being validated by the experts, if the decision is not critical or decision-maker has personal knowledge of such topic	Based on personal judgment	2
	J	Input from the specialists is accepted. But it can be challenged based on personal judgment or another expert opinion	Reliability of information source	2
	K	Inputs to decision-making process is generally accepted as is.	All information is deemed correct	2
	K	New information is always evaluated, and new decision will be discussed, in term of technical and commercial aspects	All information has to be validated	2
	K	People are scared to make decision if it reflected badly on them	escalation of commitment	5
	L	Many DM tools are used, such as Pareto, histogram, decision matrix, run chart etc.	Information is gathered systematically	
	L	The solution is decided based in the weightage of the criteria, with team consensus	group decision-making	1
	L	If decision is outside of the team scope, escalation to management is needed	management involvement for critical decision	13

	L	The root causes to be deep dived is based on the scope of problem definition	Information is gathered systematically	
	L	Problem is deep dived using cause and effect diagram, and checked against problem statement	Information is gathered systematically	
	L	Inputs are gathered carefully. Only relevant or critical inputs will be considered and investigated during DMP.	Only relevant information will be used	2
	L	Possible root causes are validated against available to data, if they are not tallied, the problem solving is restarted	Information is gathered systematically	
	M	All information is evaluated based on trustworthiness of the source	Reliability of information source	2
	N	Intuitive decision-making must have lots of knowledge and can process the information to arrive at optimal solution.	PJ requires vast knowledge	
	N	High level management normally base their decision on their intuition. Guidelines, checklist or analytical process are not used.	PJ requires vast knowledge	
	N	If there is distrust in the organization, guidelines or checklist will be needed.	Reliability of information source	2
	N	The input information will always be checked based on intuition and data.	All information has to be validated	2
	N	Decisions must always be verified at later stage to confirm the assumption made in the beginning.	previous decision must be revalidated	8
	N	New information is always analyzed and checked if current decision is still valid.	previous decision must be revalidated	8
	O	All information inputs will be evaluated based on their validity.	All information has to be validated	2
	O	Information validity is based on trustworthiness of the source	Reliability of information source	2
	O	If information inputs contradict with own knowledge, the information will be checked against different sources	All information has to be validated	2

8. What is your approach to routine decision-making process with slightly different information?	A	Applies the same decision-making ethos with routine topics	DMP routine / non-routine the same	14
	A	Unless, with past bad experience of certain decision topics due to emotional or subconscious influence		
	B	Routine decision-making is normally revolving around money, buying equipment, parts etc.		
	B	For routine technical decision, if the information and knowledge of the change is available, decision is made based on heuristics	routine uses heuristics if no more information is needed	14
	B	More information will be required if the decision situation conflicts with personal experience.	quality of information	2
	C	Routine decisions are mostly delegated to team members by empowering them	Outsource decision to group members	14
	C	Routine decision is also standardized using templates	routine decision uses standardized templates	14
	D	Decision-makers become complacent when it comes to routine decision-making.	Previous decision is rarely question	14
	F	Routine decision that has impact on timing and cost, shall be looked again using analytical process	Impact on time and cost, uses analytical process	14
	H	In aerospace, routine decisions are rare. Because the development varies wildly between projects	not many routine decisions in aerospace	14
	H	New technical decisions have to be made often without prior experience		
	H	If previous design decision was made, the decision is rarely questioned because it was one-off	Previous decision is rarely question	14
	H	Previous design decisions are always revalidated analytically based on new requirements	Previous decision is revalidated	14
	I	Not many technical routine decisions	not many routine decisions in aerospace	
	I	Routine DMP is prepared as much as possible, as early as possible	routine decision is prepared early	14
	J	Trade-off analysis is also done, but if there's conflict, it triggers detailed study	routine decision uses analytical approach	14
	K	Tendency to stick with previous decisions, in routine DMP, unless improvement is needed	Previous decision is rarely question	14
	M	Some decisions are based on previously-made decisions, they may not need to be reanalyzed.	Previous decision is rarely question	14

9. If a decision has been made and new information is provided afterwards, what do you do?	A	Adapts decision if the analysis of new information contradicts current decision	new analysis contradicts current decision	8
	A	Does not change decision if the analysis reflects poorly to the interviewee	escalation of commitment	5
	B	If there are new information, the decision will be revisited	reevaluate decision	8
	B	In early phase, when there is lack of information, decision is made based on rule-of-thumb	PJ = Incomplete information	7
	B	Decisions have to be adjusted regularly	reevaluate decision	8
	B	If new information come in, earlier analysis can no longer be trusted, and decisions have to be revisited	new analysis contradicts current decision	8
	C	If new information comes in, decision may be revisited	reevaluate decision	8
	C	If the decision context is critical, the decision has to be revisited. If otherwise, it doesn't have to	reevaluate if decision context is critical	8
	D	Impact analysis will be used to evaluate the new information	reevaluate decision	8
	D	If the consequence of the new information is big, then the decision has to be updated	change decision if impact is critical	8
	E	If a decision cannot be revised, it will not be revisited. But if it can, it will	don't evaluate if decision cannot be changed	8
	E	The decision to change judgment is made with consideration of other parties.	team consensus	1
	E	If new information comes in, and the decision context is critical, the decision will not be changed.	reevaluate if decision context is critical	8
	F	If new information contradicts from previous one, new analysis is to be made.	decision contradicts, reevaluate	8
	G	If new information comes in, it has to be analyzed and compare with previous decision.	reevaluate decision	8
	G	If the analysis has a positive impact, go with the new decision. If it has negative impact, stay with old decision.	if analysis is positive, go. If not, no go	5
	H	Normally, decisions are not normally revisited. Even if it comes with better performance, because the development time is very long in aerospace.	Normally not, unless the impact is obvious	5
	H	If the new information improves performance and has low lead time, yes.	Reconsider based on performance and time	8
	H	If the new information improves performance greatly but has high lead-time, it can be reconsidered.	Reconsider based on performance and time	8
	H	Reconsideration is based on key technical performances and cost	Reconsider based on performance and cost	8
	I	The information is looked at from its technical, cost and time impacts	Reconsider based on performance, cost and time	8
	I	The discussions have to be done internally and externally; high risk internally does not mean high risk externally	reevaluate decision	8
	I	The impact analysis is based on internal guidelines	Impact analysis based on DM procedures	8

	J	If new information comes in, it will be evaluated based on its impact and DMP must be re-open if there's impact	reevaluate if decision context is critical	8
	J	The impact analysis is a professional decision, based on experience	Based on personal judgment	1
	K	Even when the new information may cause for new decision to be made, it'll be made as long as it is the best for the project.	reevaluate decision	8
	L	New information is always considered and try to understand why this information wasn't available in the beginning.	reevaluate previous DMP	8
	L	Consider if the information is relevant to the problem space.	Reconsider based on relevance of new information	8
	L	Team will first evaluate why the first DMP didn't consider the new information in the first place	group decision-making	1
	L	Only relevant new information that is critical to the project would be included in the revision of current decision.	reevaluate if decision context is critical	8
	L	Critical new information that will be considered are the ones that can change the direction of the project	reevaluate if decision context is critical	8
	M	All new information will be evaluated based on the impact on the decision that has already been made, as a team	reevaluate decision	8
	M	A new decision will be made especially if it critically impacts (e.g.: weight, safety) the project. If it doesn't (e.g.: cost), previous decision will stay.	change decision if impact is critical	8
	N	New information will always be evaluated, and if a design change is required, then it'll be changed.	change decision if impact is critical	8
	N	The change also depends on the severity of the problem.	reevaluate if decision context is critical	8
	N	If it is critical to function, it'll be changed. If it is not, and the end of the project is near, it won't be changed.	don't change decision if impact is low	8
	N	Information is also evaluated based on the trustworthiness of the source.	Reliability of information source	2
	N	Management pressure may cause the current decision to stay if there's time pressure.	management involvement for critical decision	13
	N	From technical point of view, the change is purely based on the severity of the new information and its subsequent impact.	change decision if impact is critical	8
	O	New information will be presented and discussed with the stakeholders.	group decision-making	1
	O	If changes are required, the changes will be implemented if possible.	change decision if impact is critical	8

Appendix D: Content Analysis: Themes

	Themes	
1	Technical decision-making is overwhelmingly a group effort. The group is involved to gather information, negotiate decision and reevaluate previously-made decisions.	80%
2	Inputs to decision-making processes are judged based on the completeness of information, quality and relevance of information and reliability of the information source and the information seeker	100%
3	Not all organizations prescribe decision-making guidelines; when they do, the guidelines are normally not properly documented, and the level of detail is inconsistent	100%
4	Analytical processes and personal judgments are both utilized during technical-decision making, although analytical processes are preferred	73%
5	Sometimes, if the output of decision reevaluation has negative impact to the decision-maker or the project, new decision will not be made	27%
6	Decisions are rationalized with expert inputs, technical analysis, evidence, and feasibility studies	73%
7	Personal judgment is used if the decision is simple, information is sparse, time is a constraint or decision risk is low. Analytical processes are used if the decision is risky or critical if the analysis is complex	60%
8	If new information deviates from current data, the impact analysis will be performed based on the cost and criticality of the decision context. Decision shall be adjusted if there is a severe impact to the project and team resource is available to execute the decision	100%
9	Personal judgment is used to choose an alternative from analytical process outputs, to test whether results fit with personal knowledge and to judge whether the analytical process used may be unreliable due to incomplete information and objectiveness of the analysis	60%
10	Alternatives are re-evaluated based on the technical risk of the decision, the driving requirements, the project's timeline and budget, and the organization's vision and resources	53%
11	Organization's guidelines are not strictly followed, but as guidance to decision-making process	13%
12	Analytical process requires a lot of input information, time, and expertise	27%
13	Management may be involved in decision-making process for risky or critical decisions and if the decision falls outside of the project scope	27%
14	A routine decision approach differs greatly between decision-makers. Many decision-makers would re-use previously made decisions, while some of them will do an impact assessment based on new or updated information	67%

Appendix E: Questionnaire: Safety-critical Decision

Demographics
Position: Department manager Team leader Project manager Product manager System engineer Development engineer Other
Work experience: 0-3 years 4-7 years 8-12 years 13+ years
Industry: Automotive Medical device Space Others:
Setting the scene Your organization is developing an air filtration system that filters out dangerous particles and circulates clean air within an enclosed environment. It is a safety-critical system that ensures the users are not exposed to hazardous particles and substances. The engineering group is responsible for designing the air filtration system and integrating its sub-systems such as electrical drive, mechanical pump, chemical filtration and control systems. You are the project leader of the engineering group. Development of the air filtration control system is not within the responsibility of your organization. As outlined in your organization's product development guidelines, the control system development shall be outsourced to an internal or external supplier. It's your responsibility to evaluate the concepts provided by the suppliers. Your organization provides a set of safety standards to be adhered to during the product development process. One of the required work products is Hazard Risk Analysis. Your suppliers have been provided with the Hazard Risk Analysis and your organization's safety standards to adhere to. The constraints set by your organization in the project charter is as follows: Constraints: Development time: 5 months (buffer: +1.5 month) Development cost: EUR 525,000 (max) Unit cost: EUR400 (buffer: +EUR100) Production volume: 1,000 units

Optional: Selection Criteria: Safety requirements: Very high priority Time: Low priority Cost: Medium priority
Optional: Supplier Information Supplier A is an external company that your organization has worked together in previous projects. Supplier B is a newly setup control group within your organization. However, they are located in different location. Supplier C is an external company that has been recently added into your organization's approved supplier database.
Q1: Hazard Analysis (Ingroup bias / high technical risk) Hazard = Temporary loss of system operation Effect = Temporary illness to the users (e.g.: shortness of breath) Severity = Minor Failure likelihood = Quite low (2 on the scale of 5). Above is an excerpt from the Hazard Risk Analysis, prepared by your team of safety experts, of the air filtration system. An internationally-certified external auditor has been authorized to conduct a safety audit on your project. Upon completion of the audit, the auditor recommends that the failure likelihood of this hazard risk to be revised to "moderate" instead. You have to decide on a supplier. Before you can proceed, you have to determine whether or not to accept the analysis of your safety experts (failure likelihood = quite low) or revise the hazard risk to reflect the auditor's recommendations (failure likelihood = moderate)?
A. Agree with the expert team's analysis and proceed accordingly
B. Proceed with expert team's analysis and justify team findings with the auditor
C. Accept auditor's recommendation but with the team consensus
D. Implement external body's recommendation
E. Other (please comment):

Optional: Audit report Severity: Minor. Justification: In an enclosed environment, the only path for air circulation is through the filtration system. When the system is temporarily disabled, for less than 1 minute, users may experience temporary non-fatal breathing problem Likelihood: Moderate. Justification: Based on industry-wide data, the probability of air filtration system temporary failure is 17 PPM (part per million). Therefore, the industry best practice is to assign moderate likelihood for this kind of hazard to all suppliers. -------------------------------------Rating Legend-------------------------------------- Severity Negligible = No or negligible injury Minor = Marginal or light injury, or temporary disability Critical = Severe or permanent impairment injury Catastrophic = Fatal or life-threatening injury Likelihood-Probability Low -- Quite low -- Moderate -- Slight high -- High
Optional: Safety's expert technical justification The organization has 30 years of experience in developing air filtration system with a total of 11 products in the market. Design and production guidelines are continuously updated based on lessons learned from previous and existing products. Quality control on development and manufacturing processes are conducted frequently to ensure adherence to the guidelines. Furthermore, warranty issues arising from air filtration failure in the last 5 years have been minimal, 5 PPM (part per million). Based on these considerations, safety experts believe that setting the likelihood of this hazard to "quite low" is reasonable.
Q2: Failure control strategy In order to meet the safety requirements, supplier A has proposed to mitigate failure consequences using fail-operational mechanism. This safety mechanism transitions the system from normal mode to safe-state mode, with the use of redundant control systems. By doing so, the effects of system failures can be mitigated from temporary loss of operation to reduced-functionality operation. Based on their internal safety analysis, Supplier A implements the fail-operational mechanism using dual redundant systems. However, based on your years of experience designing redundant system, the fail-operational mechanism with triple redundancy provides higher reliability, but comes with a higher unit cost. Do you require Supplier A to revise their design to triple redundancy or trust their technical judgment with dual redundancy?
A. Require supplier A to update their design to triple redundancy
B. Propose to supplier A to revise their design to triple redundancy and review its financial impact
C. Ask supplier A to justify their technical decisions

D. Proceed with supplier A's proposal
E. Other (please comment):
Safety analysis Dual redundancy used in this project is another approach to achieve the required reliability level. This method is where dual layers of dual redundancy are built into the system, instead of single layer triple redundancy.
Q3: Cost Supplier A's design proposal is to re-use hardware components from previous projects and update the software-based fail-operational mechanism design according to the new redundancy requirements. Based on these considerations, their quotation of the control module is as following: 1. EUR525,000 for development cost 2. EUR380 for unit cost Project managers of previous projects informed you that the unit cost was EUR300, and the development cost was capped at EUR490,000 with a maximum overbudget of EUR10,000. Furthermore, based on your past experience working on redundant system, development of software redundancy only adds to the development cost, not unit cost, as long as the additional redundancy computing power is within the existing hardware performance limit. Therefore, the unit cost should be the same as before. Do you request the supplier to review the cost breakdown, or you accept their quotation at face value?
A. Set a limit to Supplier A's unit cost of EUR300 and development cost to EUR500,000
B. Review together supplier A's cost breakdown structures with your suggested cost breakdown
C. Request supplier A to justify their cost
D. Accept the quotation
E. Other (please comment):
Q4: Time Suppliers B proposes a design that uses highly reliable components to improve system fault tolerance and implements fail-operational mechanism when failure actual occurs. These combination of safety mechanisms ensure lower risk probability and hazard consequences to be under control. Supplier B promises that the control system development can be completed within 5 months. Upon discussion with your team, they believe that the timeline is ambitious and thus do not agree with the supplier's assessment. They argue that the design proposed by the supplier requires a great deal of development effort due to its complexity. Furthermore, many suppliers in previous projects had overpromised but under-delivered in terms of development time. Your team proposes to add 2 weeks buffer to the supplier's development time. Do you accept your team analysis regarding the feasibility of Supplier B timeline?
A. Request Supplier B to add 2 weeks buffer to their timeline
B. Review supplier's work breakdown structure and development schedule with your team
C. Require Supplier B to justify their proposal
D. Accept supplier’s proposed development time
E. Other (please comment):

Q5: Design proposals Supplier C proposes two different designs that have different approaches on fail-operational mechanism: 1) First design makes use of mass-produced components carried over from different industry. Because of this, the reliability of those components is not validated using field data of similar system application. Therefore, the technical risk of such implementation is considered quite high. Since the components are already several years in production, the component unit cost and total development time can be reduced significantly. Technical risk: Moderate Unit cost: EUR 300 Development time: 3 months 2) Second design uses highly reliable hardware components from previous projects. The fail-operational mechanism is based on industry-standard hardware and software redundancy. Although this approach has lower technical risk, it also comes with a high unit cost and long development time. Technical risk: Low Unit cost: EUR 500 Development time: 6.5 months Which design would you accept?
A. First design
B. Second design
Constraints: Development time: 5 months (buffer: +1.5 month) Development cost: EUR 525,000 (max) Unit cost: EUR400 (buffer: +EUR100) Production volume: 1,000 units
Objective Analysis
Q6: Decision Point Based on the selection criteria and results of supplier negotiation, Multi-Criterion Decision Analysis ranks the suppliers as follows: 1st choice: Supplier A 2nd choice: Supplier C 3rd choice: Supplier B Which of the following would you do?
A. Choose according to the ranked options
B. Re-evaluate the options based on the provided information
C. Discuss the ranked options with the team before making decision
Q7: Alternative Selection Please select your preferred supplier.
B
C

Q8: Why do you select option that differs from the Multi-Criterion Decision Analysis output? - Analytical tool is not reliable - Not all parameters are considered - Personal judgment is preferred - Input information may be incomplete - (Please state) Other reasons: And, why do you choose that particular supplier? Answer:
Q9: Alternative Selection After rounds of discussions, one of your team members has successfully argued that supplier B is the best option and managed to rally a majority of the team consensus around his decision. The team has unanimously agreed to select supplier B. Do you go with the team decision to select Supplier B?
A. Go along with team preference and choose Supplier B
B. Request the team for more justification to choose Supplier B
C. Review pros and cons of all suppliers with the team and choose supplier based on majority vote
D. Choose the supplier according to your own preference
E. Other (please comment):
Setting the scene You have previously selected a supplier to develop a control system for the air filtration system. Concurrently, your team has designed a power module that requires a power control unit. Based on the hardware architecture, your team has identified three potential control units that can fulfill the hardware requirements, as following:
Component A Component reliability: Very high Development cost: EUR 40,000 Unit cost : EUR150 Development time: 2 month Component B Component reliability: High Development cost: EUR 40,000 Unit cost : EUR150 Development time: 1 month Component C Component reliability: High Development cost: EUR 50,000 Unit cost : EUR200 Development time: 0.7 month

Project Constraint: Development time: 1.5 months Development cost: EUR 50,000 Unit cost: EUR 200 Production volume: 1000
Component A Re-use of control unit proven in previous design **Component B** New control unit from certified sub-suppliers **Component C** New control unit from other industry, can be certified for project use
Selection Criteria Component reliability: Very high priority Time: Medium priority Cost: Low priority
Objective Analysis
Q10: Decision Point Based on the selection criteria and results of selected component specifications, Multi-Criterion Decision Analysis ranks the components as following: 1st choice: Component C 2nd choice: Component B 3rd choice: Component A Which of the following would you do?
A. Choose according to the ranked options
B. Re-evaluate the options based on the provided information
C. Discuss the ranked options with the team before making decision
Q11: Alternative Selection Please select your preferred component.
A
B
Q12: Why do you select option that differs from the Multi-Criterion Decision Analysis output? - Analytical tool is not reliable - Not all parameters are considered - Personal judgment is preferred - Information input may be incomplete - (Please state) Other reasons: Why do you choose that particular component? Answer:

Q13: Team Input Your team has split preferences over Component A or B. Based on your team discussion, they prefer Component A because the component has slightly higher robustness against safety-critical failures compared to Component B. However, integrating Component A into the overall system design will significantly increase product development time. Do you agree with the team assessment?
A. Go along with team preference and choose Component A
B. Request more justification to choose component A
C. Try to convince the team to choose Component B
D. Choose the supplier according to your own preference
E. Other (please comment):
Q14: Decision Revision After spending 75% of the development budget and 90% of the development time, your supplier came back to you and report that their design has failed the component testing and will not be able to fulfill the serviceability requirements. The deadline is in 2 weeks. They require an additional 2 months and EUR70,000 to fix the issues. Based on multiple technical reviews with the supplier, there are strong evidences that the issues require major design modification and may incur more delays and cost run-offs in the future. Another option is to change to another supplier that has a good track record in delivering on time and within budget, despite the limited time left. How would you like to proceed?
A. Approve supplier's request
B. Partially approve supplier's request and warn them from any further delay and cost run-off
C. Request supplier to create an improvement plan and provide cost and deadline extension based on the agreed plan
D. Change to another supplier
E. Other (please comment):
Q15: Decision Revision One week before the end of the control unit component development, your supplier test report shows that the component does not meet its overall safety reliability target. Your customer has requested 7 prototype samples to be ready in 1 month. The supplier reported that only 6 out of 10 samples passed the reliability test. Failure to reach the target by the start of production may result in financial penalty by the customer. Based on statistical analysis, reaching the reliability target by improving the component design is almost impossible. Therefore, changing to a different component is the better technical solution, but may result in higher unit cost. How would you proceed?
A. Send 7 prototype samples to customer anyway and set lower reliability target for the component
B. Send 7 prototype samples to customer anyway, but require supplier to improve the design for future production
C. Request to delay sample delivery until supplier has improved the current design
D. Ask supplier to change the component
E. Other (please comment):

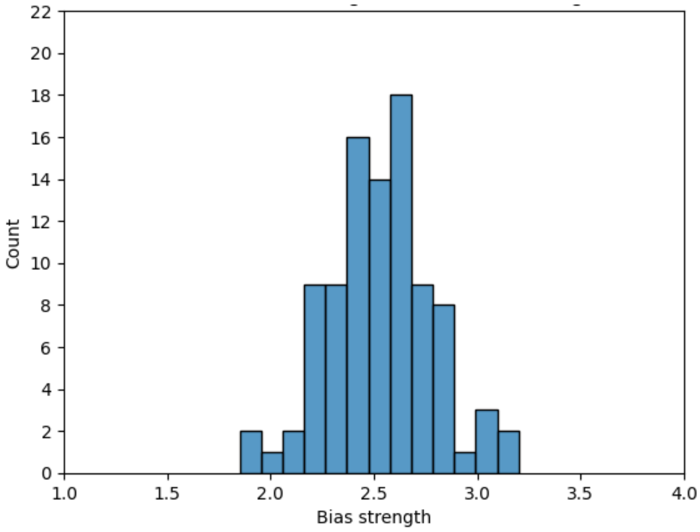
Debriefing

This questionnaire is set up to gauge the influence of human factors in technical decision making process. The collected data will be used to model the interaction between rational and behavioral components of technical decision-making in product development.

Thank you very much for your participation in this questionnaire. Your time and support are greatly appreciated. If you would like to know more about the outcomes of this research, please enter your email address below:

Appendix F: Exploratory Data Analysis: Full

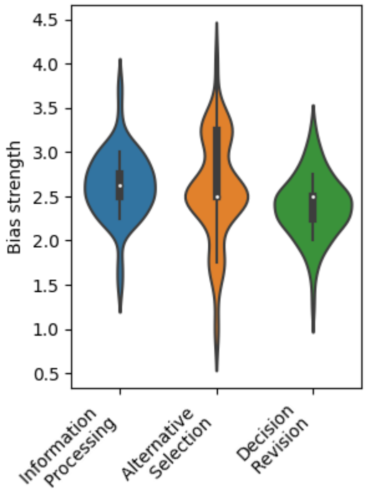
Result 1: Decision-makers were overall moderately biased during technical decision-making



Overall bias strength in the technical decision-making process

```
count    96.000000
mean      2.523438
std       0.247615
min       1.850000
25%       2.387500
50%       2.500000
75%       2.650000
max       3.200000

ShapiroResult
(statistic=0.9872356653213501, pvalue=0.483707070350647)
```

Result 2: Bias strength of decision-makers varied during the stage of the technical decision-making process



Bias strength per bias clusters

	Information Processing	Alternative Selection	Decision Revision
count	96.000000	96.000000	96.000000
mean	2.627604	2.585938	2.388021
std	0.383877	0.584704	0.355168
min	1.500000	1.000000	1.250000
25%	2.500000	2.500000	2.250000
50%	2.625000	2.500000	2.500000
75%	2.750000	3.250000	2.500000
Max	3.750000	4.000000	3.250000

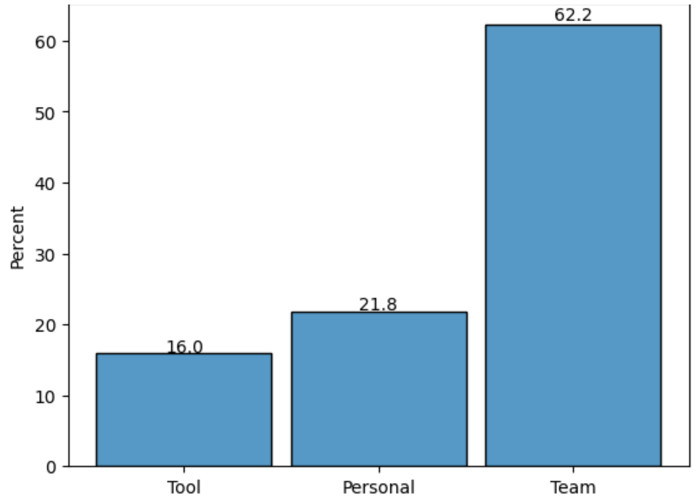
Info_Process: ShapiroResult
(statistic=0.9265804886817932, pvalue=4.5525604946305975e-05)

Alt_Select: ShapiroResult
(statistic=0.8489455580711365, pvalue=1.7927085593782977e-08)

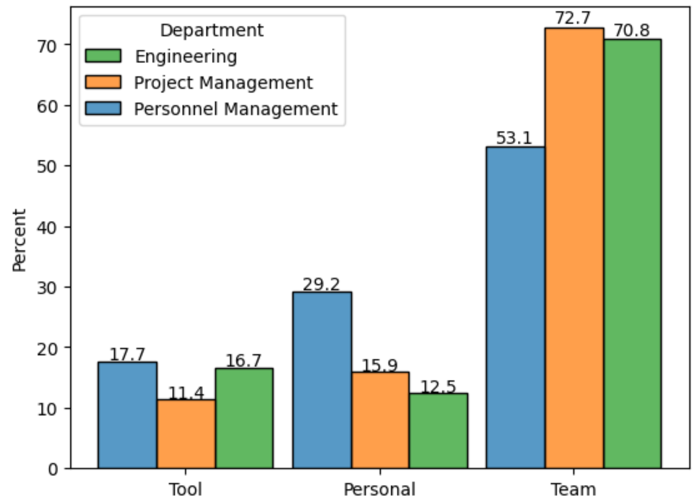
Decision_Rev: ShapiroResult
statistic=0.9506410956382751, pvalue=0.0012050856603309512)

Decision_Rev: Skewness
-0.33480847265236907

Result 3: Decision-makers most often make technical decisions as a team

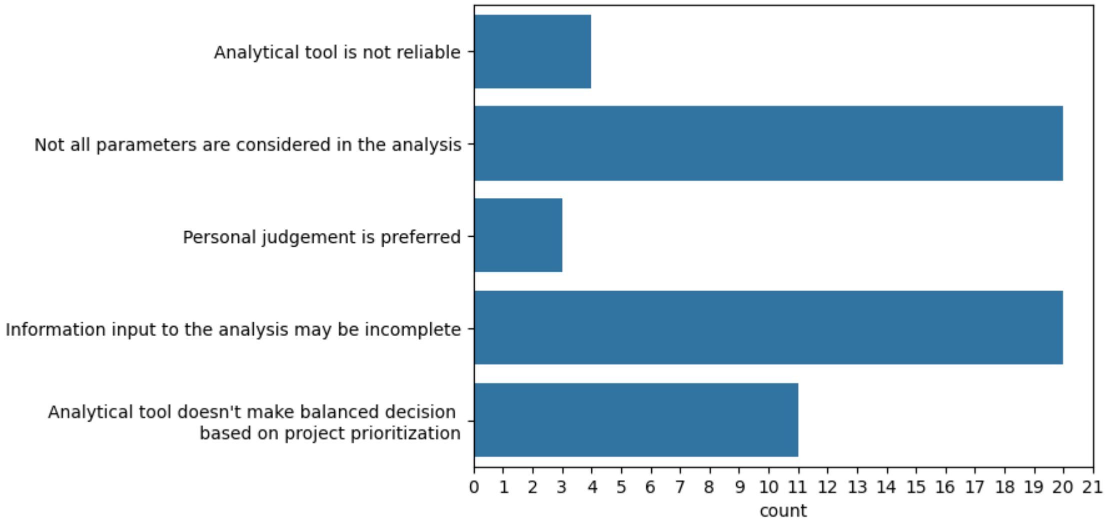


Decision-making preference



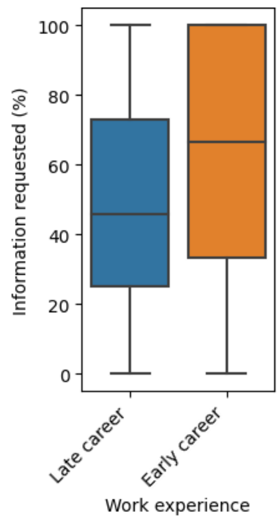
Decision-making preference according to department

Result 4: Decision-makers were skeptical of the robustness of decision analysis



Rationale for not choosing analytical tool recommendation

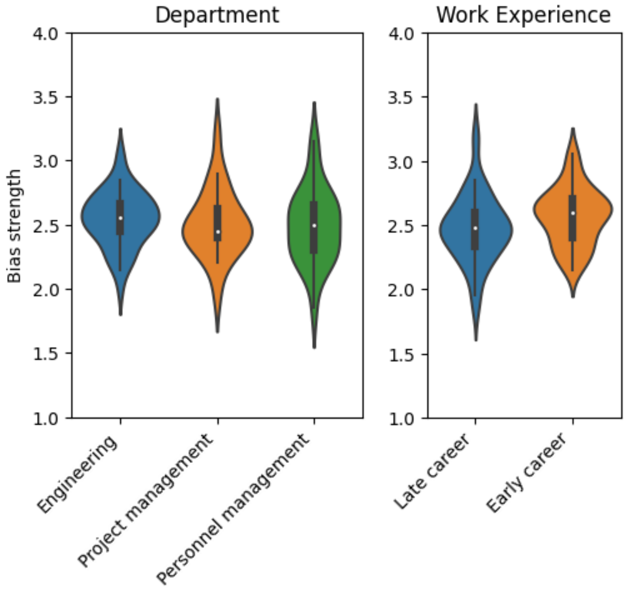
Result 5: Decision-makers did not require completeness of information to make technical decisions



Tendency to request for information

```
Complete info:
count       94.000000
mean        56.826241
std         32.699228
min          0.000000
25%         33.333333
50%         50.000000
75%         91.666667
max        100.000000

Early career  : ShapiroResult
statistic=0.8938958048820496, pvalue=0.00040178207564167768)

count       48.000000
mean        63.888889
std         32.404311
min          0.000000
25%         33.333333
50%         66.666667
75%        100.000000
max        100.000000

Late career : ShapiroResult
(statistic=0.9317346811294556, pvalue=0.009731961414217949)

count       46.000000
mean        49.456522
std         31.691130
min          0.000000
25%         25.000000
50%         45.833333
75%         72.916667
max        100.000000

MannwhitneyuResult
(statistic=825.0, pvalue=0.03376987619267503)
```

Result 6: There were no statistically significant differences of bias strength between participant demographics



Bias strength per demographic subgroups

	Count	mean	std	min	25%	50%	75%	max
Engineering	48.0	2.546	0.216	2.00	2.45	2.55	2.66	3.05
Personnel management	25.0	2.492	0.291	1.85	2.30	2.50	2.65	3.15
Project management	23.0	2.508	0.264	1.95	2.40	2.45	2.62	3.20

Shapiro-Wilk: Department

```
Engineering             (0.9846542477607727, 0.777005136013031)
Personnel management    (0.9696564674377441, 0.6363688707351685)
Project management      (0.9576796889305115, 0.41815298795700073)
```

F_onewayResult

```
(statistic=0.29513773338754024, pvalue=0.7451388956999967)
```

	Count	mean	std	min	25%	50%	75%	max
Early career	48.0	2.569	0.223	2.15	2.40	2.60	2.7	3.05
Late career	48.0	2.477	0.264	1.85	2.34	2.47	2.6	3.20

Late career : ShapiroResult

```
statistic=0.9687601923942566, pvalue=0.22656138241291046)
```

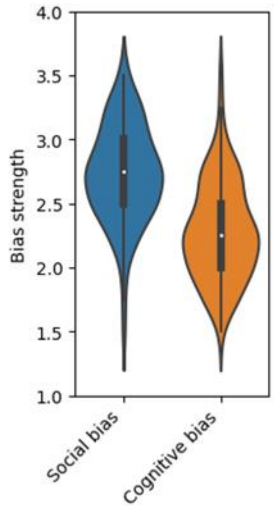
Early career : ShapiroResult

```
statistic=0.9701920747756958, pvalue=0.25771790742874146)
```

ttest

```
p-value=  0.06634024793220421
```

Result 7: Technical decision-makers were more prone to social bias than cognitive bias



Comparison between strength of social bias and cognitive bias

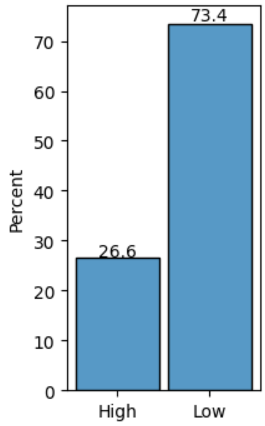
	Social_bias	Cognitive_bias
Count	94.000000	94.000000
Mean	2.739362	2.281915
Std	0.377305	0.379647
Min	1.500000	1.500000
25%	2.500000	2.000000
50%	2.750000	2.250000
75%	3.000000	2.500000
Max	3.500000	3.500000

Cognitive bias: ShapiroResult
(statistic=0.9415438175201416, pvalue=0.0003811079077422619)

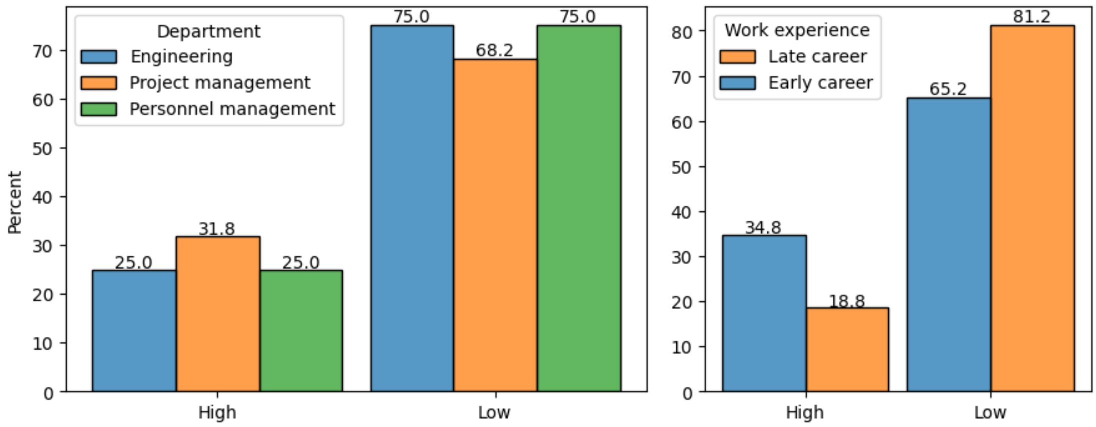
Social bias: ShapiroResult
(statistic=0.9488059878349304, pvalue=0.0010600041132420301)

WilcoxonResult
(statistic=281.0, pvalue=3.737760969388574e-11)

Result 8: Technical decision-makers were risk averse

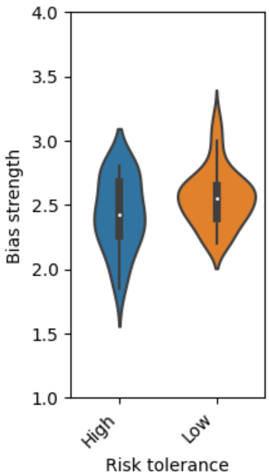


Participant's risk tolerance level



Participant's risk tolerance level according to department and work experience

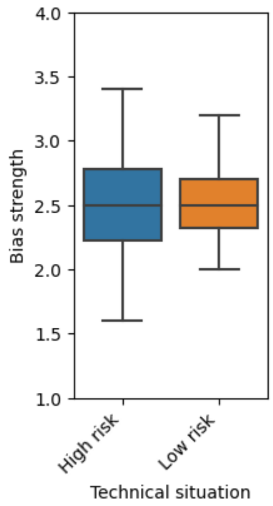
Result 9: Risk tolerance of technical decision-makers affected their bias strength



Participants' risk tolerance effects on bias strength

```
Low Risk:
count    69.000000
mean      2.558696
std       0.227835
min       2.200000
25%       2.400000
50%       2.550000
75%       2.650000
max       3.200000

High Risk:
count    25.000000
mean      2.436000
std       0.286327
min       1.850000
25%       2.250000
50%       2.450000
75%       2.700000
max       2.800000

High risk:  ShapiroResult
(statistic=0.9400309324264526, pvalue=0.14827437698841095)

Low risk:  ShapiroResult
(statistic=0.9533570408821106, pvalue=0.011718904599547386)

unpaired t-test:
p-value=  0.034162991561085786
```

Result 10: Technical risk level of a decision context doesn't affect decision-makers bias tendency



Technical situation's risk level effects on bias strength

```
Low Risk:
count    94.000000
mean      2.559574
std       0.263279
min       2.000000
25%       2.325000
50%       2.500000
75%       2.700000
max       3.200000

High Risk:
count    94.000000
mean      2.492553
std       0.411198
min       1.600000
25%       2.225000
50%       2.500000
75%       2.775000
max       3.400000


High risk:  ShapiroResult
(statistic=0.9786838293075562, pvalue=0.12801137566566467)

Low risk:  ShapiroResult
(statistic=0.9716218709945679, pvalue=0.03849051147699356)

paired t-test:
p-value=  0.17729298252872489
```