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Exploring the Influence of Behavioral Biases on Project Evaluation and Cost Management

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Abstract

This research is set within the context of behavioral finance and economics, with the goal of identifying a relationship between the deviations of expected versus actual costs and expected versus actual profit margins, and behavioral biases such as overconfidence (miscalibration and better-than-average effect), anchoring, and planning fallacy.

Project data and participant involvement were facilitated by a prominent consulting firm in the engineering and technology sector, which provided a unique dataset that allowed for the exclusion of rational explanations for cost and margin deviations. A survey was administered to 18 project managers (most of whom were involved in the provided projects) and 17 control group individuals using Qualtrics. The survey included scenarios and proxy questions designed to assess participants' levels of risk aversion, planning fallacy, miscalibration, anchoring, and better-than-average perception. Statistical methods were employed to investigate the relationships between these biases and the deviations observed.

The analysis revealed a positive relation between miscalibration and cost deviation, indicating that higher miscalibration leads to costs being higher than expected. Conversely, a negative correlation was found between miscalibration and profit margins, suggesting that margins are lower than expected in the presence of miscalibration. Moreover, a positive relationship was identified between the degree of the better-than-average effect and project managers' self-assessments of their relational skills. Additionally, the case study data analysis revealed a relationship between the use of certain decision-making methods and their outcomes. For instance, compared to democratic processes, consensus-based (unanimity), decentralized, and cascading processes perform better.

The findings suggest that integrating principles of behavioral finance into capital budgeting and project management processes can enhance project management effectiveness. Moreover, they underscore the need for ongoing review of one's technical and relational competencies to prevent miscalibration. The study also highlights the importance of expanding these surveys to include more managers and additional project data to obtain more robust statistical samples. Theoretically, this research enriches the behavioral finance literature by providing empirical evidence on how behavioral biases impact business decision-making processes.

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Chapter 1:

Foundation of Behavioral Economics

1.1 Introduction

Behavioral economics reflects a radical change away from the notion of rational decision-making that has roots in classical economics and toward a more humanistic approach to analyzing economic behavior. It does this by incorporating findings from the field of psychology to explain why people frequently make decisions that appear to be illogical, so providing a more accurate picture of human behavior in economic circumstances. According to one of the key tenets of classical economics, individuals make choices with the intention of maximizing their own utility, thereby striking an optimal balance between costs and benefits. However, behavioral economics contradicts this approach, stating that people's judgments are frequently impacted by cognitive biases, emotions, and social variables, leading to choices that depart from strict rationality (Kahneman & Tversky, 1979).

The realization that individuals do not always process information in a completely rational manner and that they are not always perfectly informed is the recognition that lays the groundwork for this field of study. According to Tversky and Kahneman (1974), human decision-making often employs heuristics, which means that it makes use of mental shortcuts and rules of thumb, both of which can result in systemic errors. For instance, according to Kahneman (2011), the availability heuristic causes people to overestimate the chance of events that are more remembered or emotionally charged, which in turn influences the decisions that people make regarding their finances and their purchases.

Prospect Theory, which was created by Kahneman and Tversky (1979), is a landmark theory in the field of behavioral economics. It argues that individuals place varied importance on gains and losses, which results in decision-making that runs counter to the expected utility theory. This theory also established the concept of loss aversion, which states that the pain of losing is psychologically more significant than the pleasure of gaining an equivalent amount, and this phenomenon influences everything from investment decisions to everyday buying decisions (Kahneman, 2011).

Over the course of the last few decades, interdisciplinary research has had a significant impact on the exponential growth of the field of behavioral economics. It has practical implications in a variety of disciplines, including marketing, policy-making, and personal finance, and it offers insights into how real people react in economic situations, as opposed to the idealized 'rational' actor (Thaler, 2015).

This field has also acquired prominence in public policy, particularly through the concept of nudging, which includes creating choices in ways that induce individuals to make better decisions without constraining their freedom of choice (Thaler & Sunstein, 2008). This field has also gained prominence in the study of behavioral economics. These kinds of treatments have been used to improve people's decisions regarding their health, their finances, and their impact on the environment.

In summary, Behavioral Economics is a branch of economics that acknowledges the complexity of human psychology to provide a more nuanced understanding of economic behavior. It is a crucial area in the study of understanding not only how individuals should make decisions, but also how they make decisions in situations that occur in the real world. For instance, this chapter delves into the exploration of human irrational behavior, examining the underlying mechanisms that manifest this irrationality. It aims to explain the concept of bounded rationality and the principles of prospect theory. Furthermore, this section will provide an analysis of heuristics and biases, offering a comprehensive understanding of their roles and impacts within the field of behavioral economics. This discussion is determining in establishing the foundational theories that will drive the subsequent analysis in this thesis.

1.2 Rationality vs. Irrationality in Decision Making

Behavioral Economics focuses on the examination of human decision-making, with rationality and irrationality serving as its core organizing concepts. The fundamental principle of classical economics is based on the notion of rational agents, individuals who possess perfect knowledge and consistently make choices aimed at maximizing their personal satisfaction (Smith, 1776). However, challenges arise when trying to explain behaviors in the actual world using this concept.

Herbert Simon introduced the concept of bounded rationality in 1957. The satisficing theory posits that individuals, despite their attempts to make rational choices, often must accept solutions that are satisfactory rather than optimal due to cognitive constraints and environmental constraints. Bounded rationality acknowledges the limitations imposed by factors such as information, time, and computational capacity on the process of human decision-making. This idea assumes that rationality does not include achieving perfection, but rather implies being pragmatic considering constraints. (Simon, 1957).

Kahneman and Tversky (1979) introduced Prospect Theory as a distinct framework for understanding decision-making under conditions of risk and uncertainty. This notion presents an extra obstacle to the traditional perspective. Prospect theory offers a different take on decision-making compared to expected utility theory. It shows that people don't always think about outcomes in a straightforward way. Instead, they give more weight to losses than to gains of the same size. This means that people are more likely to avoid risks when they might gain something but take risks when they might lose something, showing loss aversion, a phenomenon where individuals tend to have a stronger reaction to losses than to rewards. This behavior often leads to choices that don't always make logical sense, which is different from what expected utility theory suggests, where decisions are more predictable and based on the final outcome. Prospect Theory emphasizes the importance of reference points in decision-making, illustrating how the way choices are presented can significantly impact results.

These concepts, when combined, establish the basis for a more accurate elucidation of decision-making, one that acknowledges the psychological and environmental factors that impact human behavior. They challenge the notion of absolute rationality and introduce the concept of a nuanced understanding of economic decisions, influenced by both logical calculations and human biases.

1.2.1 Bounded Rationality

Herbert Simon, a leading figure in the field of behavioral economics, coined the term "bounded rationality" to explain the inherent constraints on decision-making that individuals encounter. According to bounded rationality individuals, despite their efforts to make rational decisions, are constrained by the information available to them, their cognitive limits, and the limited time they have to make choices. Simon claimed that these limitations encourage humans to pursue satisfactory solutions instead of the optimal ones proposed by conventional economic theory, which assumes flawless knowledge, boundless cognitive capacities, and no time restrictions. This notion has fundamentally transformed the comprehension of decision-making processes, emphasizing the significance of psychological and practical variables in economic behavior.

Unlike Simon's concept of constrained rationality, classical economic theories are based on the idea of total rationality. Classical and neoclassical economics are based on rational choice theory, which believes that individuals have complete information and infinite cognitive powers. It also implies that individuals consistently make choices that maximize their utility (Becker, 1976). This model depicts economic agents as completely rational and driven by self-interest, systematically assessing all possible choices to determine the most advantageous one. Simon's perspective on bounded rationality acknowledges the limitations of human decision-making, such as limited access to information, cognitive biases, and time constraints. As a result, decisions are often satisfactory rather than optimum.

The term “satisficing”, introduced by Herbert Simon, embodies a fundamental element of constrained rationality. Satisficing is a strategy in which individuals strive for a solution that is sufficient or satisfactory, rather than pursuing the optimal option as suggested by models of perfect rationality.

This method is a result of the restrictions in our mental capacities and the limitations of our surroundings, which frequently make it impossible or impracticable to optimize.

Conversely, optimization, as described in conventional economic theories, presumes that humans possess the capacity to assess all conceivable alternatives and their consequences to make the most advantageous choice. Optimizing needs comprehensive information, an unlimited amount of time, and boundless cognitive processing capabilities, circumstances that are rarely fulfilled in real-life situations. Satisficing recognizes the practicality of human decision-making: we frequently select from a restricted range of choices and information, driven by what appears to be satisfactory within a certain situation, rather than what would be optimal in an ideal scenario. This idea is more suited to the decision-making process in ordinary life, where there are constraints on time, information, and cognitive resources.

There are numerous instances in the real world where people use satisficing as a decision-making strategy. Work seekers frequently apply to multiple opportunities that fulfill specific criteria, such as location, pay, and work description, rather than doing an exhaustive search for the ideal job that perfectly corresponds with all their abilities and career objectives. (Rynes & Gerhart, 1990)

Satisficing is observed in food shopping as a common occurrence in daily life. Shoppers generally choose products that meet their requirements adequately, considering aspects such as price, brand recognition, and quality, rather than meticulously comparing every available alternative in the store to make the most optimum choice. (Payne & Johnson, 1988).

These examples demonstrate how satisficing serves as a pragmatic strategy for decision-making in situations where the ability to achieve an ideal solution is impeded by limitations such as time, information, and cognitive resources.

Heuristics play a crucial role in constrained rationality. Heuristics are cognitive strategies that people employ to streamline the process of making decisions, especially when faced with intricate and unpredictable circumstances (Tversky & Kahneman, 1974). These shortcuts facilitate quick decision-making by diminishing the cognitive burden associated with processing extensive quantities of information. Although heuristics are effective, they can also result in systematic biases and errors in judgment. Understanding the practical consequences of limited rationality requires grasping this idea, which recognizes the constraints in human cognitive processing and the tactics used to deal with these constraints.

The concept of bounded rationality has extensive implications in various fields such as economics, business, and policy-making. This undermines the conventional economic premise of complete rationality and emphasizes the importance of recognizing human limitations in decision-making.

Bounded rationality in economics fundamentally changes our comprehension of individual behavior within markets. Behavioral economics, which is based on the concept of bounded rationality, investigates instances where individuals do not behave perfectly rationally. It helps us understand phenomena such as market anomalies and decision-making that are not optimal (Thaler, 2015).

Within the business domain, acknowledging the concept of constrained rationality influences approaches in marketing, product development, and the analysis of consumer behavior. Companies employ behavioral insights to design products and services that are in line with consumers' cognitive limits and biases (Ariely, 2008).

Bounded rationality is a significant factor in the development of effective interventions in policy decisions. The notion of "nudging" as introduced by Thaler and Sunstein (2008), utilizes behavioral insights to guide individuals towards improved choices while preserving their freedom of choice. This methodology has been implemented in fields such as public health and environmental preservation.

There are numerous examples in these domains. For example, the notion of "choice architecture" entails organizing choices in a manner that steers persons towards desirable results (Thaler & Sunstein, 2008). Recognizing investor biases such as overconfidence and loss aversion in finance provides valuable insights for risk management and investing strategies (Kahneman & Tversky, 1979).

Adopting limited rationality improves decision frameworks by matching them with the cognitive abilities and behavioral tendencies of humans. It acknowledges that individuals may not consistently make optimal choices but can be influenced towards actions that align with their best interests, leading to more efficient regulations, corporate practices, and economic models.

In summary, Herbert Simon's concept of constrained rationality challenges standard economic theories that assume total rationality. Bounded rationality acknowledges that humans, in their search for rational decision-making, have cognitive limitations and contextual constraints that impede their capacity to consistently make optimal decisions. Alternatively, people frequently opt for satisficing, which involves pursuing solutions that are deemed satisfactory within the limitations they face. Deviation from the optimization of behavior is essential for comprehending decision-making in the real world.

Moreover, the function of heuristics as cognitive shortcuts under limited rationality offers an understanding of how individuals streamline intricate decision-making procedures. Although heuristics can accelerate decision-making, they can also add biases and errors, underscoring the fragile equilibrium between efficiency and accuracy.

The ramifications of constrained rationality have wide-ranging effects in diverse domains, including economics, business, and policymaking. Recognizing the constraints of human capabilities results in the development of decision frameworks that are both pragmatic and efficient. It emphasizes the necessity for interventions, like as nudging, that steer individuals towards improved choices without infringing on their autonomy.

1.2.2 Prospect Theory

Prospect Theory, developed by Kahneman and Tversky (1979), is a groundbreaking concept in behavioral economics. It presents a new framework for understanding how individuals make decisions under conditions of uncertainty and risk. Unlike traditional economic theories that assume rational utility maximization, Prospect Theory supposes that people evaluate potential outcomes relative to a reference point, often making choices based on the perceived gains and losses from that reference point. This theory challenges conventional economic thinking by offering a more nuanced perspective on human decision-making, emphasizing the psychological and emotional factors that influence choices (Kahneman & Tversky, 1979).

One of the core principles of this theory is the framing effect, a concept that reveals the significant impact of presentation and context on decision-making processes. The framing effect refers to the phenomenon where people's choices are influenced by the way information is presented rather than just by the information itself. In other words, the same objective information can lead to different decisions depending on the frame through which it is viewed. This concept is critical in understanding human behavior, as it demonstrates that the rationality of decision-making is often bounded by the perception of the information provided.

For example, consider a medical decision-making scenario. When patients are presented with treatment options in terms of survival rates, they are more likely to opt for the treatment than if the same probabilities are framed in terms of mortality rates (McNeil, Pauker, Sox, & Tversky, 1982). This demonstrates how the framing of options as gains or losses can significantly alter the choice, despite the underlying probabilities remaining constant.

The framing effect, as exemplified by Kahneman and Tversky in 1984, especially in the domain of financial decision-making, presents a notable deviation from classical economic theories. Classical approaches, such as the anticipated utility theory, claim that individuals evaluate risks by considering the objective values of the ultimate outcomes. Prospect Theory, on the other hand, presents an alternative mathematical expression for assessing choices, placing greater emphasis on the psychological effects of gains and losses rather than their exact magnitudes.

This theory posits that when individuals are confronted with investment choices, their decision-making process is significantly influenced by the way these options are framed, particularly in terms of potential gains and losses. Notably, individuals exhibit a tendency to take greater risks to avert losses than to attain equivalent gains. This behavior stems from the concept of loss aversion, a cornerstone of Prospect Theory, which suggests that losses evoke a stronger emotional reaction than an equivalent amount of gains.

Loss aversion implies that the pain or dissatisfaction individuals experience from losing a certain amount is typically more intense than the pleasure or satisfaction derived from gaining the same amount. For example, the discomfort of losing $100 often surpasses the happiness of gaining $100. This disproportionate impact of losses over gains profoundly influences financial behavior. Investors might hold onto losing stocks longer than advisable, hoping to avoid the realization of a loss, or they might shy away from sound investment opportunities if there's any significant risk of loss. This aversion to loss can lead to suboptimal financial decisions, as it often overrides an objective analysis of potential risks and rewards. Such behavior contrasts sharply with the assumptions of classical economic theories, which posit that individuals evaluate outcomes based on a balanced view of gains and losses.

The difference in functional structure signifies a substantial departure from conventional economic models. Classical benchmarks primarily focus on the objective utility obtained from end results, but Prospect Theory incorporates a subjective element to the computation of utility. It acknowledges that the emotional significance of losses and profits is not proportional or balanced; losses have a greater impact than gains, resulting in decision-making tendencies that deviate from the logical, linear frameworks of traditional economics.

The implications of the framing effect extend beyond individual decision-making to policy-making and marketing. For instance, how a policy is framed can significantly affect public opinion and compliance. Similarly, marketers often use framing strategies to influence consumer behavior, such as highlighting the benefits of a product or the disadvantages of not using it.

The value function, a central element of Prospect Theory developed by Daniel Kahneman and Amos Tversky in 1979, fundamentally changes the conventional understanding of decision-making, particularly under risk and uncertainty. This function represents how individuals perceive gains and losses, providing a more psychologically accurate model of human behavior compared to traditional economic theories.

At its core, the value function is characterized by several key features. Firstly, it is defined in terms of changes from a reference point rather than final states of wealth or welfare, suggesting that people think in terms of gains and losses rather than absolute outcomes (Kahneman & Tversky, 1979). This implies that the same outcome can be perceived differently depending on what is considered the starting point or the status quo.

Secondly, the value function is concave for gains and convex for losses, indicating diminishing sensitivity. This means that the perceived value of a gain or loss decreases as the magnitude increases. For instance, the difference in value between $100 and $200 is more significant to an individual than the difference between $1,100 and $1,200, even though both differences are $100. Empirical studies have shown that the pain of losing is psychologically about twice as powerful as the pleasure of gaining (Tversky & Kahneman, 1991). This asymmetry explains why individuals often exhibit risk-averse behavior in gains and risk-seeking behavior in losses.

The value function also incorporates a feature known as the endowment effect, which describes how individuals ascribe more value to things merely because they own them (Kahneman, Knetsch, & Thaler, 1990). This effect, tied to the concept of loss aversion, implies that the disutility of giving up an object is greater than the utility associated with acquiring it.

In practical terms, the value function has significant implications for understanding economic behavior. For instance, it helps explain why people might hold onto losing stocks for too long (hoping to avoid realizing a loss) or sell winning stocks too quickly (to lock in gains). It also sheds light on consumer behavior, like the reluctance to switch brands or try new products, as these choices often involve perceived losses.

In the framework of Prospect Theory, reference points play an essential role in shaping decision-making processes. These reference points establish a baseline or status quo against which gains and losses are measured, fundamentally influencing how individuals perceive and evaluate outcomes. The notion of reference points diverges from traditional economic models, which typically focus on absolute outcomes rather than relative changes.

The significance of reference points lies in their ability to frame the perception of a situation. For instance, a person's current wealth can serve as a reference point when evaluating financial decisions. If an individual considers their current wealth as a baseline, any amount above this level is perceived as a gain, and any amount below it is seen as a loss (Kahneman & Tversky, 1979). This perspective significantly alters the way individuals assess risk and make choices. It implies that the same objective outcome can be viewed differently depending on what is considered the 'normal' or starting position.

Prospect Theory has been widely applied in diverse real-life situations, demonstrating its practical significance across multiple domains. Within the domain of financial markets, investors frequently exhibit conduct that aligns with the expectations of the theory, particularly in relation to their aversion to losses. This phenomenon is apparent when investors exhibit a tendency to retain underperforming companies for a longer duration than logical models would indicate, in the hopes of avoiding acknowledging a loss. Conversely, they prefer to sell outperforming stocks too quickly in order to secure their profits (Shefrin and Statman, 1985).

The ideas of Prospect Theory are evident in the insurance sector and in consumer choices about warranties. Individuals frequently exhibit a greater propensity to allocate funds towards insurance or extended warranties than what traditional economic models would anticipate. The observed behavior, which is influenced by the unequal emphasis placed on possible losses compared to equivalent gains, illustrates loss aversion. (Kahneman & Tversky, 1979).

The impact of Prospect Theory can be observed in marketing and pricing strategies. Marketing leverages the framing effect, a crucial element of the theory, to influence consumer decisions. For instance, the way a discount is presented, whether to prevent a loss or as an opportunity for gain, can have a substantial impact on consumer behavior. This method capitalizes on the theory's understanding of how framing can manipulate perceptions and choices (Tversky & Kahneman, 1991).

The framing effect is a crucial factor in patient decision-making within the healthcare field. Patients may make different choices based on the presentation of medical therapy alternatives in terms of survival or fatality rates, even if the underlying probability is identical. The study conducted by McNeil, Pauker, Sox, and Tversky (1982) examined this issue, demonstrating how Prospect Theory helps elucidate decision-making in situations with significant risks.

The principles of the theory also apply to public policy, specifically in the context of environmental issues. Presenting policy alternatives in terms of negative outcomes rather than positive outcomes can have a more significant influence on public opinion and behavior. This application employs the principle of loss aversion to incentivize behaviors that promote conservation and environmental protection.

The acceptance of proposals in negotiations and dispute resolution can be strongly influenced by the way they are presented. The idea suggests that solutions offered as avoiding losses are generally more acceptable to people than those presented as maximizing gains, due to its understanding of human decision-making processes.

Furthermore, consumer behavior exhibits the endowment effect, which is the phenomenon of individuals attributing higher value to products once they possess them. The phenomenon, as investigated by Kahneman, Knetsch, and Thaler (1990), illustrates that individuals frequently require a higher price to sell a commodity they possess compared to what they would be ready to pay for it if they did not possess it, even if the product is the same.

The diverse instances across several industries emphasize the influence and significance of Prospect Theory in comprehending and forecasting human conduct in practical circumstances, ranging from financial choices to policy formulation and consumer behavior.

After delving into Prospect Theory and the concept of bounded rationality, we now move on to another critical part of behavioral economics: heuristics and biases. These concepts are inherently linked with the previously described principles. Bounded rationality acknowledges that cognitive constraints frequently hinder individuals from making completely rational choices, while heuristics and biases provide a more comprehensive account of how these constraints emerge in everyday decision-making. Heuristics are cognitive shortcuts or general principles that individuals employ to simplify intricate tasks, although they frequently result in systematic inaccuracies or prejudices. These biases refer to consistent deviations from normative or rational judgment and decision-making. Through the analysis of heuristics and biases, we can develop a more profound comprehension of why humans frequently make decisions that, although appearing unreasonable or inefficient, are predictable outcomes of these cognitive shortcuts.

1.2 Overview of Biases and Heuristics

Even though behavioral economics is always changing, two important ideas stay the same: biases and heuristics. These two ideas shed light on the fascinating complexities of how people make decisions and explain why people don't always make the choices that standard economic models say they should.

At its core, behavioral economics is based on the idea that people are not always the completely rational actors that classical economic theory portrays. Instead, they are affected by cognitive biases, which are regular deviations from what is normal or logical in judgment that can cause distorted perception or bad judgment (Kahneman & Tversky, 1974). People's biases show how complicated the mind is by showing how people make choices and judgments that don't always make sense.

Cognitive biases include a wide range of things, each of which sheds light on a different aspect of how people act. For example, confirmation bias makes people look for information that backs up what they already believe and ignore evidence that goes against what they think. When people are making decisions, anchoring bias shows how they tend to focus too much on the first piece of information they see. The availability heuristic (Tversky & Kahneman, 1974) shows that people tend to overestimate how likely something is based on how easy it is for them to remember it.

Along with biases, people use heuristics, which are brain shortcuts or rules of thumb, to make complicated decision-making processes easier. Heuristics are mental tools that help people make quick decisions when they don't have enough time or knowledge (Gigerenzer & Todd, 1999). People can make decisions and judgments quickly with these mental shortcuts, but they also make mistakes and systematic flaws more likely.

One well-known heuristic is the availability heuristic, which says that people figure out how likely something is by how easily they can remember similar events. This mental shortcut can lead to biases when people make decisions by giving too much weight to recent or highly charged events (Tversky & Kahneman, 1974).

Researchers have found other seminal heuristics that affect human decision-making. The representativeness heuristic, established by Tversky and Kahneman (1974), is an example. By comparing an occurrence to mental prototypes, this heuristic estimates its probability. People may overestimate the possibility of an event if it matches their stereotypes or past experiences, regardless of statistical probability. The gambler's fallacy occurs when people assume that previous occurrences affect future events in random sequences.

The anchoring heuristic is another. It refers to humans' tendency to base decisions on the first piece of information, the ‘anchor'. Even arbitrary initial price offers in negotiations might influence later evaluations and conclusions. This heuristic can skew estimations and predictions by favoring the anchor value and ignoring new information that should cause a review.

Heuristics and biases go hand in hand and often work together to affect how people make decisions. Heuristics are mental shortcuts that people use to make complicated choices easier to make. Biases are the flaws that people make when they depend on these mental shortcuts. For example, confirmation bias might make someone only look for information that reinforces up what they already think, while the availability heuristic helps them remember cases that support what they already believe.

Understanding how these two concepts interact is important for understanding how people make decisions in everyday life. It also shows how important it is to be aware of the limits of human perception and the fact that people can make choices that are beneficial and detrimental.

In the next few sections, we'll go into more detail about specific biases and heuristics, looking at where they come from, the way they manifest, and what they mean in real life in various domains. By figuring out the complicated web of biases and heuristics, we learn important things about the human mind. This lets us make more accurate guesses about behavior and come up with solutions that help people make better decisions.

1.3.1 Heuristics

Heuristics help individuals navigate the overwhelming amount of information they encounter daily, allowing them to arrive at decisions in a more time-efficient manner.

There are two primary levels of heuristics. First-Level Heuristics: these are intuitive strategies that people use without conscious effort. They are automatic and often based on readily available information. Second-Level Heuristics: these heuristics involve more conscious thought and deliberation. They may be employed when the situation requires a deeper analysis. Understanding the concept of heuristics is fundamental to grasping how individuals make decisions in the real world, as they underpin many aspects of human judgment and behavior (Gigerenzer & Todd, 1999).

The availability heuristic is a mental shortcut where individuals assess the likelihood of an event based on how easily it comes to mind. In other words, people tend to judge the probability of an event based on the ease with which they can recall similar instances from their memory (Tversky & Kahneman, 1974). For example, if someone can easily recall news reports of plane crashes, they may overestimate the likelihood of a plane crash when considering air travel. This heuristic can lead to biased judgments because it relies on the individual's exposure to specific information rather than objective probabilities.

Seminal research by Tversky and Kahneman has shed light on various heuristics – mental shortcuts that simplify complex decision-making processes. These heuristics, while efficient, often lead to systematic biases and deviations from rational judgment. The most notable among these are the availability heuristic, the representativeness heuristic, and the anchoring heuristic.

The representativeness heuristic involves making judgments about the probability of an event based on how similar it is to a prototype or stereotype. Individuals categorize objects, events, or people into mental categories and assess the likelihood of an item belonging to a category based on how well it matches the prototype (Tversky & Kahneman, 1974). This heuristic can lead to errors in judgment because it neglects base rates and objective probabilities. For example, if someone meets a person who fits the stereotype of a librarian (e.g., wears glasses and is introverted), they may mistakenly assume that the person is a librarian, even if the base rate of librarians in the population is low.

The anchoring heuristic is a cognitive bias where individuals rely too heavily on the first piece of information encountered when making decisions. This initial information, known as the anchor, influences subsequent judgments and decisions, often causing individuals to insufficiently adjust from the anchor when new information becomes available (Tversky & Kahneman, 1974). For example, in negotiations, the first offer made can serve as an anchor, affecting the final agreed-upon price. If the initial offer is high, the final price may still be higher than it would have been without the anchor.

These heuristics are essential in understanding human decision-making processes, as they provide insights into how individuals simplify complex choices. However, they can also lead to systematic biases and errors in judgment, illustrating the delicate balance between efficiency and accuracy in decision-making.

Heuristics play a pivotal role in simplifying complex decision processes and expediting judgments, making them a cornerstone of human decision-making. Firstly, heuristics simplify decision processes by reducing the cognitive load associated with complex choices (Gigerenzer & Todd, 1999). When individuals face overwhelming amounts of information, heuristics allow them to quickly filter and prioritize relevant details. For example, the availability heuristic enables individuals to focus on readily available information, streamlining the decision-making process.

Secondly, heuristics facilitate rapid judgments by offering intuitive and easily applicable rules of thumb (Gigerenzer & Gaissmaier, 2011). These mental shortcuts eliminate the need for exhaustive analysis, allowing individuals to make decisions efficiently. The representativeness heuristic, for instance, guides individuals to make judgments based on resemblance to prototypes, expediting assessments.

Moreover, heuristics often rely on familiarity and accessibility. People tend to use heuristics based on their prior experiences and knowledge, further streamlining decision-making (Tversky & Kahneman, 1974). For instance, when estimating the risk of a familiar activity like driving, individuals may use their personal experiences as a heuristic, simplifying their judgment process.

Heuristics also interact with emotional and intuitive aspects of decision-making (Kahneman & Frederick, 2002). They align with fast and automatic thinking, enabling quick judgments based on intuition. This speeds up the decision-making process in situations where immediate responses are necessary. Reliance on heuristics in decision-making can lead to cognitive biases and systematic errors, which are critical aspects of understanding the limitations of these mental shortcuts.

One well-documented cognitive bias associated with heuristics is confirmation bias (Nickerson, 1998). When individuals use heuristics to simplify complex information, they may accidentally seek out information that confirms their preexisting beliefs or judgments while ignoring contradictory evidence. This confirmation bias can reinforce existing biases and prevent individuals from making objective decisions.

In the context of real estate, professionals often rely on heuristics to estimate property values. One common heuristic is the anchoring heuristic. When appraisers first encounter information about a property, such as its listing price, that initial figure can serve as an anchor. Subsequent appraisals tend to be influenced by this anchor, even if it doesn't accurately reflect the property's value (Northcraft & Neale, 1987).

For example, if a house is listed at a price significantly higher than its actual market value, appraisers may still base their estimates on the inflated anchor. This anchoring bias can lead to overestimation of property values, affecting real estate transactions.

In capital budgeting decisions within organizations, heuristics can play a significant role. For instance, when evaluating investment projects, decision-makers may use the representativeness heuristic. They might assess the potential success of a project based on how closely it resembles past successful projects (Kahneman & Lovallo, 1993).

For instance, if a company previously had success with a particular type of project, decision-makers may be biased toward choosing similar projects in the future, assuming they will also be successful. This representativeness heuristic can lead to missed opportunities and suboptimal investment decisions.

In both real estate cost appraisal and capital budgeting, heuristics simplify decision-making by offering quick and intuitive ways to assess options. However, these examples also highlight the potential for cognitive biases, such as anchoring and representativeness, to influence judgments and lead to suboptimal outcomes.

1.3.2 Biases

Cognitive biases refer to consistent and predictable patterns of deviation from rationality or the norm in judgment, which frequently result in errors in perception, cognition, or decision-making (Tversky & Kahneman, 1974). These biases are a result of the inherent constraints in human information processing and memory retrieval. Cognitive biases result in persons straying from completely logical reasoning and decision-making processes, resulting in predictable errors in judgment, perception, and problem-solving.

Cognitive biases significantly influence the decision-making process by impacting the way individuals collect, analyze, and use information. They can exert an impact on both the selection and the way information is processed. Cognitive biases frequently result in departures from logical and reasonable decision-making, thereby injecting systematic errors into the process. Some of the most prevalent forms of cognitive biases are optimism bias, overconfidence bias, planning fallacy bias, hindsight bias, and status quo bias. These biases are regarded as some of the most important in cognitive psychology and behavioral economics due to their pervasive influence on human decision-making and behavior.

Optimism bias, a cognitive bias, refers to the tendency of individuals to systematically underestimate the likelihood of negative events occurring and overestimate the likelihood of positive events. This bias can lead to overly optimistic predictions and decisions, which may result in suboptimal outcomes. Research by Sharot (2011) has shown that optimism bias is a pervasive and robust phenomenon, affecting various aspects of life, from health and finance to decision-making under uncertainty. A classic example of this is noticeable in the field of personal finance, where individuals frequently exhibit exaggerated optimism about their financial circumstances in the future. Because of this bias, people tend to assume that their income will increase more than it actually will, which causes them to spend more and conserve less. Numerous studies have been conducted on this phenomenon, such as Weinstein's (1980) research, which discovered that people often have an excessive amount of optimism when it comes to their own dangers compared to others.

Overconfidence bias is the inclination of individuals to overrate their own capabilities, expertise, or the precision of their assessments (Lichtenstein et al., 1982). This bias can lead to unjustified overconfidence, causing individuals to make judgments without sufficiently evaluating potential risks or uncertainties. This type of bias is especially noticeable among traders and investors in the financial sector. Overconfident investors frequently trade more than is necessary because they think they are better at selecting stocks. This reduces market efficiency and results in less-than-ideal investment decisions. (Daniel, Hirshleifer, Subrahmanyam, 1998),

The planning fallacy bias refers to the tendency to underestimate the time, costs, and hazards involved in future activities or events (Kahneman & Tversky, 1979). Individuals often exhibit excessive optimism about their capacity to accomplish tasks punctually and within financial constraints, resulting in inadequate preparation and impractical anticipations. An illustration of this phenomenon can be observed in the construction business, where project timelines and budgets are commonly undervalued. Buehler, Griffin, and Ross (1994) elucidate this bias in their study, demonstrating the propensity of individuals to exhibit excessive optimism in their time projections, hence resulting in project delays and budgetary excesses.

Hindsight bias, or the "I knew it all along" effect, is the inclination to view previous events as more predictable than they truly were (Fischhoff, 1975). Individuals often tend to overestimate their capacity to predict future events after they have already taken place, resulting in inaccurate evaluations of past occurrences. In legal settings, this bias can affect jury decisions, where jurors might believe that the defendant should have foreseen the outcome of their actions, even if it was not reasonably predictable.

Status quo bias refers to the inclination to favor keeping the existing order of affairs rather than implementing changes, especially when the potential advantages of change surpass the associated drawbacks (Samuelson & Zeckhauser, 1988). Individuals frequently stick to known choices due to apprehension of ambiguity. A typical example is consumer behavior, particularly in subscription-based services. Samuelson and Zeckhauser found that consumers tend to stick with their current subscriptions, like cable or internet plans, even when better options are available, due to their preference for the familiar and fear of potential losses from change.

As we end this introductory chapter, we acknowledge the limits of the traditional Homo economicus model and embrace the more realistic depictions of human behavior provided by behavioral economics. Now, we will focus on applying these concepts to important economic areas. The next chapter explores the complexities of capital budgeting and project management. In particular, regarding project management we will be helped by studies in the real estate field, these two worlds are linked by frequent cost appraisals. Here, the observations derived from the field of behavioral economics become particularly noticeable. We will examine how cognitive biases and decision-making influenced by heuristics, as previously mentioned, appear in various areas, frequently resulting in notable disparities between theoretical forecasts and actual results.

Chapter 2: Capital Budgeting and Project Management Practices

2.1 Introduction to Capital Budgeting

Capital budgeting significantly impacts the long-term performance of firms. These estimates and assumptions about market trends and other factors provide the essential basis for decision-making. However, decision-makers have only limited direct control over these aspects. Capital budgeting can be seen as a process of constructing reality, rather than making a rational choice. Studies indicate that decision-makers possess a restricted degree of influence over their own biases in this process of constructing (Russo & Schoemaker 1992). Post-completion auditing of capital investments is widely used in large firms and primarily serves the objective of organizational learning (Huikku 2008). However, the fact that it exists could be seen as a reaction to a repeating series of unsatisfying choice outcomes. In the following section, we will explore the capital budgeting decision-making process. By understanding this process and its implications, we can gain valuable insights into how organizations approach the challenging task of allocating resources to projects.

2.2 Capital Budgeting Process

Capital budgeting is the process in which a business determines whether projects are worth pursuing. Thus, as a first measure, the projected cash inflows and outflows of a project are estimated. Subsequently, they undergo scrutiny to determine if the project will generate value beyond a specific benchmark after incurring costs. This is significant since only projects of this nature should be pursued. Nevertheless, around 70% of companies are willing to accept investment proposals that do not match the necessary minimum rate of return, for reasons such as strategic considerations or legal limitations (Schönbohm & Zahn, 2012).

The primary objective of capital budgeting is to discover and evaluate investment possibilities that have the potential to increase the overall value of a company. These opportunities can include mergers and acquisitions, as well as investments in tangible assets. However, the selection of these opportunities is subject to limitations imposed by the market or top management, and the focus is on choosing the options that offer the greatest value. Subsequently, these projects are included in a yearly capital budget that must align with the strategic objectives of a firm, as most capital budgeting choices have long-term implications for the company.

Some researchers define three stages of the process while others call for up to five stages. (Burns & Walker, 2009). In this paper, we will consider 5 phases: identification, selection, authorization, implementation, performance measurement, and control (Schönbohm & Zahn, 2012).

2.2.1 Phase 1: Identification

Project ideas can be formulated through two approaches: firstly, ideas can arise either from a bottom-up perspective or from a top-down perspective, and secondly, they can be motivated either by a favorable circumstance or by a requirement for financial backing. The investment ideas derived from a bottom-up approach align with the opportunities identified by operational management.

Hence, it is not reasonable to assume that middle management will put up strategic recommendations. Instead, strategic investment ideas with high value are more likely to originate from senior management who possess a comprehensive understanding of the firm and its growth. Moreover, it is necessary to allocate funds for purposes such as replacing outdated assets or expanding into new markets.

Following an initial search of proposals, a preliminary screening and filtering process is conducted. This process aims to identify any conflicts with strategic goals (if the suggestions originated from the bottom-up approach), as well as assess the adequacy of the hurdle rate, risk levels, and practicality. The company's data-gathering efforts are essential, including the usage of accounting or cash-flow methodologies, the condition of the decision support system, and how senior management handles forecasts.

2.2.2 Phase 2: Selection and Selection Tools

At this stage, the surviving proposals undergo a comprehensive evaluation that includes a detailed analysis of cash flow projections, risk assessment, market demand, cost of capital, timing of investments, personnel requirements, and an initial execution strategy. (Kalyebara & Amhed, 2011). The most commonly employed evaluation algorithms include net present value, followed by internal rate of return and payback time. The weighted average cost of capital is used to determine the cost of capital or hurdle rate, while the capital asset pricing model is used to determine the cost of equity.

The Net Present Value (NPV) approach is a widely recognized and essential tool in capital budgeting that assists firms in choosing and assessing investment projects. The concept of NPV is based on the notion that a logical investor should distribute resources toward projects that optimize the current value of anticipated future cash flows. This approach involves the application of an appropriate discount rate, such as the firm's cost of capital, to calculate the present value of future cash flows (Brigham & Ehrhardt, 2017). Cost of capital encompasses the cost of both equity and debt, weighted according to the company's preferred or existing capital structure, To calculate the NPV, one must deduct the original investment from the present value of anticipated cash streams during the duration of the project. If there's one cash flow from a project that will be paid one year from now, then the calculation for the NPV of the project is as follows:

$$NPV = \frac{\text{Cash flow}}{(1+i)^t} - \text{initial investment}$$

where:

i = Required return or discount rate

t = Number of time periods

If analyzing a longer-term project with multiple cash flows, then the formula for the NPV of the project is as follows:

$$NPV = \sum_{t=0}^{n} \frac{R_t}{(1+i)^t}$$

where:

R_t = net cash inflow - outflows during a single period

i =discount rate or return that could be earned in alternative investments

t = number of time periods

A positive NPV signifies that the project is projected to yield returns that are above the minimum rate of return above zero, hence increasing the wealth of the firm's owners.

The preference for NPV is shared by both academics and practitioners due to many reasons. Firstly, it considers the concept of the time value of money, which acknowledges that the true value of a dollar obtained in the future is lower than that of a dollar received now (Ross, Westerfield, & Jordan, 2017). Furthermore, NPV aligns the interests of stakeholders with investment decisions and is in line with the purpose of maximizing shareholder wealth. Furthermore, it facilitates the evaluation of projects with different magnitudes and timeframes, enabling businesses to effectively distribute resources among competing options (Gitman & Zutter, 2019).

Net Present Value (NPV) is not without limitations. One significant constraint is its assumption of certainty in future cash flows, an often unrealistic expectation in real-world scenarios (Brealey, Myers, & Allen, 2020). Additionally, the choice of discount rate in NPV calculations introduces a subjective element, varying according to the risk profile of the project (Ross, Westerfield, & Jaffe, 2019). Despite these shortcomings, NPV remains an indispensable tool for financial managers, offering a systematic and financially sound framework for project selection and resource allocation (Brigham & Ehrhardt, 2021)

The Internal Rate of Return (IRR) approach is a crucial financial analysis tool used to evaluate investment projects. It determines the discount rate at which the Net Present Value (NPV) of the project's cash flows becomes zero. The formula and calculation used to determine this figure are as follows:

$$0 = \mathrm{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+IRR)^t} - C_0$$

where:

C_t= Net cash inflow during the period t

C_0 = Total initial investment costs

IRR = The internal rate of return

t = The number of time periods

Using the formula, one would set NPV equal to zero and solve for the discount rate, which is the IRR. The IRR is a measure that represents the annualized percentage return expected from an investment project. Decision-makers frequently assess the computed IRR against a pre-established hurdle rate, usually the company's cost of capital, in order to ascertain the project's economic feasibility.

The attractiveness of IRR stems from its straightforwardness and instinctive appeal. A project is considered acceptable if its internal rate of return (IRR) is more than the cost of capital. This indicates that the project generates returns that are higher than the needed rate of return. Moreover, the internal rate of return (IRR) enables a straightforward comparison of projects, as it is expressed as a percentage. This makes it easily understandable for both financial professionals and individuals without financial expertise (Gitman & Zutter, 2019)

Nevertheless, the IRR does have some limitations. When the cash flows of a project have unusual patterns, it might lead to the emergence of various internal rates of return (IRR), which makes interpretation more complex (Van Horne & Wachowicz, 2008). In addition, the internal rate of return (IRR) does not take into account the magnitude of the investment or offer a precise quantification of the project's worth in monetary units.

The Weighted Average Cost of Capital (WACC) is a crucial instrument in capital budgeting that offers a complete method to evaluate the financial viability of investment projects. WACC is a metric that calculates the average cost of the funds used by a company, including the different amounts of equity and debt in its capital structure (Brealey, Myers, & Allen, 2017). WACC is calculated by assigning weights to the cost of stock, the cost of debt, and the cost of alternative forms of financing based on their market prices or book values, as follows:

$$\text{WACC} = \left(\frac{E}{V} \times Re\right) + \left(\frac{D}{V} \times Rd \times (1 - Tc)\right)$$

where:

E = Market value of the firm's equity

D = Market value of the firm's debt

$V=E+D$

Re=Cost of equity

Rd=Cost of debt

Tc=Corporate tax rate

The discount rate in the Net Present Value (NPV) calculation determines if the anticipated returns from a project are higher than the cost of capital, enabling decision-makers to make informed judgments (Gitman & Zutter, 2019).

The key advantage of WACC is its capacity to integrate the costs of both equity and debt, offering a comprehensive perspective on the cost of capital utilized in a project. The Weighted Average Cost of Capital (WACC) is determined by taking into account the firm's capital structure. It indicates the balance between the cost of stock, which involves the reduction of ownership, and the cost of debt, which includes interest payments and risks associated with leverage. Moreover, WACC considers market dynamics, rendering it a flexible benchmark that may be modified to mirror evolving market circumstances.

Nevertheless, the WACC technique is not without problems. The precise determination of the separate elements of WACC, namely the equity cost, may be susceptible to uncertainty (Van Horne

& Wachowicz, 2008). Moreover, the process of determining suitable weights for different sources of capital can be intricate, particularly for companies with varied capital structures.

The Capital Asset Pricing Model (CAPM) is a highly regarded and essential instrument in capital budgeting, assisting companies in evaluating and controlling the risk linked to investment projects. The CAPM, which was first formulated by Sharpe (1964), Lintner (1965), and Mossin (1966), offers a structure for determining the necessary rate of return on an investment project, sometimes referred to as the cost of equity capital (Brealey, Myers, & Allen, 2017). The assumption underlying this concept is that investors anticipate a return that adequately compensates them for the time value of money and the inherent systematic risk associated with an investment. The CAPM utilizes the risk-free rate, the market risk premium, and the beta coefficient of the investment to determine the cost of equity. The risk-free rate is the return you could get on a completely risk-free investment, like government bonds. It represents the time value of money without any risk. The market risk premium is the additional return that investors expect for taking on the risk of investing in the overall market instead of a risk-free asset. The formula for calculating the expected return of an asset, given its risk, is as follows:

$$ER_i = R_f + \beta_i(ER_m - R_f)$$

where:

ER_i= expected return on investment

R_f= risk-free rate

β_i = beta of the investment

($ER_m - R_f$) = market risk premium

It compensates for the uncertainty associated with the stock market. The beta coefficient of the investment measures how sensitive an investment's returns are to changes in the overall market. A beta of 1 means the investment moves in line with the market, while a beta greater than 1 suggests it's more volatile, and a beta less than 1 indicates it's less volatile. Beta, specifically, is the slope coefficient obtained through regression analysis of the stock return against the market return. You can use the following regression equation to estimate the beta of the company:

$$\Delta S_i = \alpha + \beta_i \times \Delta M + e$$

where:

ΔS_i = change in price of stock i

α = intercept value of the regression

β_i=beta of the i stock return

ΔM = change in the market price

e = residual error term

The strength of the CAPM model is in its methodical approach to evaluating risk. The CAPM provides a means to calculate the cost of equity capital for a project by considering the systematic risk associated with the overall market. This estimation is tailored to the project's specific risk profile (Gitman & Zutter, 2019). The model offers a precise and measurable indicator of the anticipated return on equity, assisting decision-makers in comparing investment projects and assessing their appeal.

However, CAPM is not without limitations. It assumes that the relationship between an investment's return and the market is linear and constant, which may not always hold true in real-world scenarios (Van Horne & Wachowicz, 2008). Additionally, the model relies on estimates and assumptions, such as the risk-free rate and the market risk premium, which can introduce variability in the calculated cost of equity. Nevertheless, CAPM remains an invaluable tool for project evaluation, offering a structured approach to determining the required rate of return based on the project's inherent risk.

As a result of this complete screening procedure, only the most strategically sound and financially feasible initiatives are chosen to proceed to the next step. Subsequently, the selected initiatives are presented to the higher levels of management for the pivotal stage of approval and authorization. In this context, leaders of the organization evaluate the results of the thorough study in relation to the company's strategic goals, willingness to take risks, and the resources at their disposal.

2.2.2 Phase 3: Authorization

At this stage of the capital budgeting process, companies face the challenge of allocating their limited capital resources to various proposed projects. This allocation process is influenced by factors such as capital rationing and predetermined capital budgeting targets. Essentially, it's about deciding which projects will become a reality within the constraints of available funds.

To make these decisions, companies assess the capital demand of each project and compare it with the sources of capital supply they have at their disposal. These sources include:

Depreciation Reserves: these are funds set aside over time to replace or maintain assets as they wear out. They are considered an internal source of capital.

Retained Earnings: these are profits that a company has accumulated and retained for reinvestment. Retained earnings also constitute an internal source of capital.

Loans: companies may secure loans from financial institutions, which represent an external source of capital.

Corporate Bonds and Shares: issuing corporate bonds or shares allows companies to raise external capital by selling these financial instruments to investors.

One crucial factor influencing this decision-making process is the cost of capital. For example, companies have limited control over the cost of debt because it is influenced by prevailing financial market conditions. (Dean, 1951)

Once the question of financing is addressed, companies proceed to rank the projects based on various criteria, including strategic importance, expected returns, and associated risks. Risks can be categorized into general risks (such as market risk, inflation, interest rate fluctuations, and foreign exchange rate risk) and specific risks unique to each project.

To assess and manage these risks, companies often use techniques like sensitivity analysis or risk mapping, which ranks risks based on their potential impact and likelihood. This helps in identifying which risks require special attention and potential risk responses. These responses may include adjustments to discount rates or cash flows to account for the perceived risk.

Finally, after addressing questions related to financing, prioritization, and initial implementation plans, the projects that are deemed the most promising and aligned with the company's objectives are authorized for full-scale implementation.

2.2.4 Phase 4: Implementation

During the implementation phase, a comprehensive implementation plan is created and distributed throughout the business. The responsibility for carrying out the implementation lies with operations management, while senior management is responsible for overseeing it. This stage can adhere to the conventional methodology of project management. Firstly, it is necessary to implement a job breakdown framework. The project is divided into work packages and specific activities or tasks to be executed.

Subsequently, a competent individual is designated for each duty, together with certain time periods and a budget allocation. Ultimately, milestones, which refer to scheduled meetings or deadlines by which specific deliverables must be completed, are established. Typically, a project management committee is established to oversee the planning, execution, and reporting of a project. (Kalyebara & Amhed, 2011).

2.2.5 Phase 5: Performance Measurement and Control

There are three types of measurement that can be used to evaluate a project's performance. Initially, closely monitoring the period immediately before and after the commencement of implementation to identify and address any unforeseen issues.

Furthermore, it is essential to closely monitor the implementation process to effectively manage any delays in scheduling and excessive expenditures, as well as to address any issues that may arise. Lastly, following the conclusion of the project (post-audit), the main objective is to collect insights for future projects. Additionally, there will be a limited evaluation of the accuracy of projections provided by project initiators. To verify the accuracy of the findings, it is common practice to compare estimates with actual outcomes, such as profits, costs (including initial expenses or ongoing cash withdrawals), volumes, time, or rates of return, etc. (Schönbohm & Zahn, 2012).

Despite the apparent significance of performance monitoring and control, there is a startling lack of action in this domain. In 1991, Gordon and Myers discovered that 76% of the participants in their study conducted post-audits. However, these post-audits were not conducted regularly, were not adjusted for risk, and were not well documented. As a result, they did not meet the criteria for being considered a standard capital budgeting technique.

2.3 Introduction to Project Management

Project management, according to the Project Management Institute (PMI), is the organized implementation of information, expertise, tools, and methods to carry out project tasks and accomplish particular goals within established limitations (PMI, 2017). It is crucial to comprehend that project management and capital budgeting, while interconnected, have separate roles in the domain of organizational decision-making.

Although both fields have the shared objective of maximizing value and attaining strategic goals, they differ in terms of their specific focus and extent. Capital budgeting generally focuses on doing financial analysis and making investment decisions about the allocation of long-term assets. It evaluates the financial viability of new projects by using financial indicators such as Net Present Value (NPV), Internal Rate of Return (IRR), and Weighted Average Cost of Capital (WACC) to assess investment options. The main objective of capital budgeting is to ascertain the financial feasibility of projects and ensure their alignment with the financial objectives of the company.

However, project management involves a wider range of tasks, including the planning, execution, and control of projects to achieve certain goals within predetermined limitations (Schwalbe, 2018).

Financial considerations are a crucial part of project management, but they encompass more than just financial aspects. They also involve stakeholder management, resource allocation, risk assessment, quality control, and overall project governance. Project management focuses on ensuring the timely completion, cost-effectiveness, and stakeholder satisfaction of projects.

Capital budgeting functions as the primary evaluation process for investment proposals, identifying whether projects are financially viable and consistent with the organization's capital allocation policy. Project management, however, is responsible for overseeing the implementation of these approved projects, with a specific focus on operational factors, resource allocation, and risk management necessary for project completion.

2.3.1 Project Life Cycle

The project life cycle represents the systematic progression of a project from its inception to its conclusion, encompassing a series of distinct phases that collectively guide the project from idea to execution and ultimately closure (Schwalbe, 2018). Understanding the project life cycle is integral to effective project management, as it provides a structured framework for organizing and managing project activities. We will consider 4 phases: initiation, planning, execution and monitoring, and closing. (PMI, 2017)

The first phase, 'Project Initiation,' marks the inception of the project. During this stage, project managers and stakeholders define the project's objectives, scope, and initial constraints. It is here that project charters are developed, and stakeholders' expectations are clarified. The initiation phase sets the foundation for the entire project by aligning it with organizational goals and ensuring that it is strategically sound.

Following initiation, the 'Project Planning' phase takes center stage. This phase involves the development of a comprehensive project management plan, outlining the project's scope, schedule, budget, resource allocation, and risk management strategies. The work breakdown structure (WBS) is crafted during planning, providing a detailed breakdown of project tasks and dependencies. Successful project planning establishes a roadmap for project execution and facilitates effective resource allocation.

Once the project plan is in place, the 'Project Execution and Monitoring' phase commences. In this phase, project teams execute the planned activities and tasks to deliver the project's desired outcomes. Effective leadership, team coordination, and communication are critical during this phase to ensure that project goals are met, and quality standards are upheld. Continuous monitoring and control mechanisms are implemented to track progress, identify deviations, and take corrective actions as needed.

Finally, the 'Project Closure' phase signifies the culmination of the project. Here, project outcomes are formally delivered to stakeholders, and the project is evaluated against predefined criteria for success. Lessons learned are documented, and knowledge transfer occurs, contributing to organizational learning and improvement for future projects. Project closure ensures that all project activities are completed, and resources are released for allocation to new endeavors.

In summary, the project life cycle provides a structured framework that guides projects through initiation, planning, execution, and closure. Understanding each phase's distinct objectives and activities is fundamental to effective project management, ensuring that projects are delivered on time, within budget, and to the satisfaction of stakeholders.

2.3.2 Project Management Tools and Best Practices

Successful project management relies on a repertoire of essential tools, processes, and industry best practices that enable efficient planning, execution, and completion of projects. These indispensable materials are crucial for effectively handling the intricacies and uncertainties inherent in project work.

Project managers utilize a diverse range of tools to optimize project workflows and improve communication. Tools such as Gantt charts, Critical Path Analysis (CPA), and Project Management Software (PMS) aid in the visualization of project timelines, identification of essential tasks, and monitoring of progress (Schwalbe, 2018). For instance, Gantt charts were pivotal in the successful management of complex projects like the Hoover Dam and the Interstate Highway System (Kerzner, 2019). Risk assessment tools, such as risk matrices and decision trees, facilitate the assessment of potential hazards and provide information for the development of risk mitigation measures. Common project risks include scope creep, cost overruns, and missed deadlines, often arising from inadequate risk management (Hillson, 2017).

Project management techniques offer systematic frameworks that direct project teams throughout the project life cycle. The PMBOK® Guide from the Project Management Institute (PMI) and Agile methodologies such as Scrum and Kanban are widely acknowledged (PMI, 2017). While the PMBOK® provides extensive instructions for traditional project management procedures, Agile methodologies prioritize iterative and adaptive methods. For example, companies like Spotify and Atlassian have effectively implemented Agile approaches to foster innovation and adaptability (Sutherland, 2020).

The project management field benefits from industry best practices, which are derived from the successful experiences of previous projects. Best practices involve issues such as stakeholder engagement, risk management, and quality assurance. Effective communication with stakeholders, for example, was crucial in the redevelopment of the London King’s Cross station, aligning project objectives with stakeholder expectations (Turner, 2020). A well-defined change management approach helps to effectively handle project transitions and minimize opposition to change, as evidenced in IBM’s transformation projects (Kotter, 2018).

By integrating these tools, processes, and industry best practices, project managers may maximize project outcomes, boost productivity, and minimize risks. However, common mistakes such as underestimating resource needs, poor communication, and neglecting stakeholder input can derail projects (Pinto, 2019). Choosing the most suitable tools and processes, based on industry standards, is crucial for tailoring project management strategies to the unique requirements of each project.

Now, as we transition from the broader canvas of project management best practices to a more focused lens, we enter the nuanced world of software development methodologies. In the subsequent section titled "Software project management: Agile, Scrum, and Waterfall", we explore how these specific methodologies embody the principles of project management within their unique frameworks.

2.3.3 Software Project Management: Agile, Scrum, and Waterfall

In the realm of software development, various methodologies are employed to structure, plan, and control the process of developing information systems. Among these, Agile, Scrum, and Waterfall are predominant, each with distinct attributes and implications for project management.

Agile methodology is characterized by its iterative and incremental approach, where projects are divided into small parts that are completed in work sessions, ranging from the design phase to testing and quality assurance. The Agile approach is lauded for its flexibility and responsiveness to changing project requirements. It promotes collaboration and cross-functional teamwork, which can lead to greater product quality and user satisfaction. However, the lack of a defined endpoint can sometimes lead to project scope creep, and the continuous nature of the work can lead to burnout among team members if not managed properly. Agile's adaptive nature may also make it difficult to predict final project costs and timelines, which can be a drawback for budgeting and strategic planning (Cohen, D., Lindvall, M., & Costa, P., 2004).

Scrum, a subset of Agile, organizes software development within a framework of iterative practices and predefined roles, such as the Scrum Master and Product Owner. Scrum enhances team productivity by breaking down complexity into manageable sprints, leading to incremental product development and frequent reassessment of tasks. This can result in quicker project turnovers and a better alignment with user needs, as Scrum teams often reassess project directions. However, Scrum's emphasis on self-organization can sometimes lead to issues if team members are not disciplined or experienced enough to handle the autonomy effectively. Additionally, Scrum's sprint-based approach can lead to rushed work if not managed properly (Schwaber, K., & Sutherland, J., 2011).

Waterfall methodology, on the other hand, is a more traditional approach where the project is structured into sequential phases, and each phase must be completed before the next one begins. This method is praised for its clear structure and well-defined stages, which can facilitate understanding and contractual clarity. It works well for projects where requirements are well understood and unlikely to change. However, its rigidity can be a significant disadvantage in today's fast-paced and change-prone development environments. The Waterfall model is often criticized for its inflexibility and for the late stage at which it incorporates user feedback, which can lead to a higher risk of product misalignment with user needs and potentially costly late-stage changes (Royce, W. W., 1970).

Each of these methodologies has its strengths and weaknesses, and the choice between them often depends on project requirements, client needs, team expertise, and organizational culture. The literature on software development methodologies continues to expand, reflecting the evolving challenges and strategies that practitioners encounter in the field.

2.4 Cognitive biases regarding capital budgeting and project management

When striving for efficient capital budgeting and project management, it is crucial to recognize that these fields have inherent restrictions. These restrictions frequently arise as a result of the impact of cognitive biases and heuristics that are inherent in the human decision-making process. Biases, such as excessive confidence, the tendency to be overly optimistic, and the influence of not useful initial reference points, can have a substantial effect on the process of making capital budgeting decisions and managing projects. Excessive confidence can prevent from accurately assessing the potential dangers associated with a project, whereas a tendency towards optimism can lead to unduly positive projections of costs and time. Conversely, anchoring can cause decision-makers to become fixated on initial project plans, impeding their capacity to adjust to changing conditions.

The forthcoming chapter will provide a comprehensive analysis of the cognitive biases of overconfidence, optimism bias, and anchoring. It will specifically investigate their impact on the decision-making procedures in both capital budgeting and project management. This study will elucidate the psychological elements that impact decision-making, frequently diverging from reasonable and objective evaluations. Organizations can enhance the accuracy and reliability of their capital budgeting decisions and project management procedures by using techniques and safeguards to limit the impact of cognitive traps associated with biases.

As we move to the next chapter, it becomes clear that identifying and dealing with these cognitive biases is essential not just for reducing constraints but also for maximizing the success and results of capital budgeting and project management efforts. By providing decision-makers with the necessary knowledge and tools to manage these cognitive hazards, businesses may enhance their ability to achieve strategic objectives and fully capitalize on their investments and projects.

Chapter 3: Capital Budgeting and Project Management Biases

3.1 Introduction to Biases in Decision-Making

Making decisions is a crucial process in the fields of capital budgeting and project management, and it is greatly impacted by a variety of conditions, both irrational and rational. This chapter explores the complexities of decision-making in different domains, with a particular emphasis on the impact of cognitive biases. The first chapter of this thesis covered behavioral economics, which has shown that human decision-making frequently deviates from what conventional economic theory predicts. These variations are especially noticeable in settings with high stakes and complexity, such as project management and capital budgeting. In many domains, choices are influenced greatly by the cognitive biases of those involved in addition to being primarily based on calculation and strategic planning. Comprehending the underlying dynamics that propel decision-making processes in these domains requires an awareness of and comprehension of these biases.

As we learn from the existing literature, overconfidence, anchoring, and the planning fallacy are the three primary cognitive biases that will be discussed in this chapter and how important they are to capital budgeting and project management.

Project managers make most of the decisions; they determine how projects are carried out and how resources are allocated. They are not impervious to biases, though. It is essential to comprehend the scope and effects of these biases on project managers. Their choices frequently have a significant impact on the general well-being and performance of the businesses they represent, in addition to the initiatives they oversee.

Utilizing insights from behavioral economics, this chapter seeks to clarify these biases in the context of capital budgeting and project management. We can gain a better understanding of the frequently subtle factors that influence judgments in these important sectors by investigating these biases.

3.2 Scope and Relevance of Study

This section of the thesis aims to establish the scope and underline the relevance of the study on biases in capital budgeting and project management. The focus on these areas is underpinned by the recognition that cognitive biases can significantly influence the decision-making process, affecting the efficiency and effectiveness of project outcomes.

A notable gap exists in the literature specifically addressing the impact of cognitive biases on project managers. Given their critical role in decision-making processes in capital budgeting and project management, this gap is significant. The decisions of project managers have far-reaching consequences, influencing not only the immediate project but also broader organizational strategies and outcomes.

To address this under-researched area, the study will explore existing literature on project management and incorporate insights from real estate. This approach is justified by the similarities in decision-making processes and challenges in both fields. Real estate literature offers a wealth of knowledge on decision-making under uncertainty, particularly concerning cost appraisal, risk assessment, and project valuation. These areas closely align with the core responsibilities of project management and capital budgeting.

Both project management and real estate require professionals to make predictions and judgments about future costs and potential risks. The methods and challenges in these appraisals are similar, making insights from real estate literature applicable to project management.

The decision-making processes in real estate involve biases similar to those encountered in project management, including overconfidence in market trend predictions or anchoring in investment decisions. These parallels provide a valuable perspective for understanding how such biases can affect project management decisions.

Transitioning from the fundamental principles of capital budgeting and project management, it's crucial to delve into the psychological underpinnings that can subtly yet significantly influence decision-making processes in these areas. Cognitive biases, such as overconfidence, anchoring, and planning fallacy, play a pivotal role in shaping the judgments and choices of managers, often leading to suboptimal outcomes.

Overconfidence bias, a common trait among decision-makers, leads to an exaggerated belief in their ability to understand and control future events. This often results in underestimating risks and overestimating the success of a project (Kahneman & Tversky, 1979). Anchoring bias, on the other hand, occurs when individuals heavily rely on initial information (the "anchor") and inadequately adjust to subsequent information. This can lead to skewed financial estimates when initial figures unduly influence final budget decisions (Tversky & Kahneman, 1974). Lastly, the planning fallacy, identified by Kahneman and Tversky (1979), refers to the tendency to underestimate the time, costs, and risks of future actions, while overestimating the benefits, often resulting in optimistic timelines and budgets that are rarely met. Understanding and acknowledging these biases is essential for effective decision-making in capital budgeting and project management.

3.3 Overconfidence

The term "overconfidence" has been extensively employed in the field of psychology since the 1960s. The concept of overconfidence in psychology is primarily associated with the study of calibration and probability assessment (Brenner et al, 1996). It is sometimes used interchangeably with one of the various types of miscalibration. Economists often expand the scope of this concept by studying overconfidence within the framework of positive illusions, namely the better-than-average effect.

Several psychological reasons for overconfidence emerge in the literature. Keren (1997) divides them into cognitive and motivational ones (overconfidence as a self-motivating mechanism). Similarly, Russo and Schoemaker (1992) name cognitive, psychological, and motivational areas. Cognitive reasons include biases, which may be alleviated by accelerated and accurate feedback, counterargumentation, or careful consideration of the problem. The motivational side exposes the need to believe in one's efficacy to make progress.

The misalignment of confidence and accuracy within the cognitive process might be attributed to numerous factors. Overconfidence can result from flaws in the cognitive process of generating responses that are not easily retrievable from memory, or from the mistaken perception that solutions are retained in memory when they are not. The reconstructive nature of memory and perception allows for the occurrence of errors, unknown to the individuals involved. Furthermore, the discriminative aspect of memory, which prioritizes the more significant items, leads to further errors in producing responses, while keeping the levels of confidence unaffected (Fischhoff et al. 1977).

One reason for overconfidence is confirmation bias, which is well-studied in the literature. This prejudice is influenced by both cognitive and motivational factors. Confirmation bias occurs when experiment participants heavily rely on confirming evidence that supports their selected hypothesis while disregarding contradictory arguments. The enhanced calibration resulting from the explicit directive to take into account both types of evidence as outlined by Fishhoff et al. (1980) provides compelling evidence for the influence of confirmation bias on the development of overconfidence. Furthermore, confidence judgments are predominantly influenced by the quantity and intensity of supporting evidence, rather than contradictory evidence, which has minimal or no impact on the formulation of confidence judgments (Fischhoff et al. 1980).

In the upcoming section, we will delve deeper into the nuances of overconfidence, examining it through two distinct lenses: overconfidence as miscalibration and overconfidence as the 'better-than-average' effect. We will explore these concepts by analyzing examples that demonstrate how to numerically detect both forms of overconfidence.

3.3.1 Miscalibration and Better Than Average Effect

The better-than-average impact and miscalibration are two primary aspects of overconfidence. Estimates of quantities that are unknown and estimates of quantities that may one day be discovered can both exhibit miscalibration. To determine how much an interval estimate is miscalibrated, apply the fractile approach below:

"Please include the following approximations for your forecast. The correct response to the question (such as those concerning the length of the Nile River or the Dow Jones Euro Stoxx 50's value in a given week) needs to be...

Lower bound: not falling short of the lower bound with a high likelihood of 95%.

Upper bound: not going over the upper bound with a high likelihood of 95%."

People's probability distributions are typically found to be overly tight in studies that use this fractile approach to investigate such judgments of uncertain variables (Lichtenstein & Philips, 1982; Keren, 1991). The percentage of surprises, or the percentage of true values that fall outside the confidence interval, is found to be higher than 10% in studies where participants are asked to state a 90 percent confidence interval for a number of uncertain quantities. This is because 10% is the percentage of surprises that an unbiased person would have when estimating 95 percent upper and lower bounds.

These quantile estimates of probability distributions are frequently elicited for continuous numbers that are unclear, typically pertaining to general knowledge issues. Instead of the 10% predicted by well-calibrated judges, hit rates in many studies utilizing 90 percent confidence intervals are less than 50%, resulting in surprise rates of 50% or greater.

In other research, the degree of miscalibration is measured by having participants respond to multiple-choice questions. Subjects are then asked to indicate the likelihood that their response is accurate, as demonstrated by the direct probability judgment example below:

“Charles Darwin or Charles Dickens: who was born first?

To what extent are you certain (please indicate with a number between 50% and 100%)?”

Typically, the percentage of right answers is less than the given probability (Lichtenstein et al., 1982).

The better-than-average impact is another aspect of overconfidence. A typical question designed to elicit this effect is:

“Consider your driving skills. Do you think that you have above-average skills compared to the other people in this room?”

The most important discovery is that individuals believe their abilities to be above average. Research by Taylor and Brown (1988) shows that people's perceptions of themselves are excessively positive. A significant example of this proof is the belief that one's own abilities or good personality traits make one superior to others. A frequently used example is the finding that 82% of students place themselves in the top 30% of drivers in terms of driving safety (Svenson, 1981). The question of whether the better-than-average impact can be rationally explained has recently come up for discussion in the literature (Merkle and Weber, 2009).

3.3.2 Factors Influencing Overconfidence

Overconfidence is shaped by various factors, including gender, social and cultural contexts, and expertise. Each of these factors has been extensively researched, providing a nuanced understanding of how overconfidence manifests in different scenarios.

In the realm of gender, the relationship between overconfidence and gender has been a focal point of research. One seminal study by Barber and Odean (2001) in "Boys will be boys: Gender, overconfidence, and Common Stock Investment" explores how gender influences investment decisions. They found that men were more overconfident in their investment decisions than women, leading to more frequent trading and lower net returns. This gender disparity in overconfidence is attributed to a variety of factors, including societal norms and psychological predispositions. The study underscores the far-reaching implications of overconfidence in financial decision-making and highlights how gender norms can influence economic behavior.

Social and cultural factors also play a significant role in shaping overconfidence. Geert Hofstede's research on cultural dimensions, particularly his work in "Culture's Consequences: Comparing Values, behaviors, institutions, and Organizations across nations" (2001), offers profound insights into how cultural contexts influence confidence. Hofstede's study reveals that cultures with high individualism, such as the United States, tend to foster greater overconfidence compared to collectivist cultures like Japan. This variation can be attributed to the cultural emphasis on individual success and assertiveness in individualistic societies. These findings are critical in understanding how cultural norms and values shape not only personal behavior but also broader societal trends in confidence and decision-making.

Age has been identified as a significant factor influencing overconfidence, with several studies suggesting variations in overconfidence levels across different age groups. Research indicates that younger individuals often exhibit higher levels of overconfidence compared to older adults. This phenomenon is attributed to a variety of factors, including experience, cognitive development, and risk perception. For instance, Moore and Healy (2008) suggest that younger individuals are more prone to overestimate their abilities and knowledge, a pattern that tends to diminish with age as individuals accumulate more life experiences and knowledge. Similarly, Malmendier and Tate (2005) found that younger executives often display higher levels of overconfidence in their decision-making, impacting corporate policies and risk-taking behaviors. This age-related variance in overconfidence highlights the importance of considering demographic factors when assessing decision-making processes and potential biases.

Expertise, while generally associated with better judgment and decision-making skills, surprisingly also correlates with overconfidence in certain contexts. This relationship is multifaceted and can vary depending on the domain and the individual's level of true expertise. In their influential work, Kruger and Dunning (1999) in "Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments" delve into this complexity. They found that individuals with moderate to high levels of expertise often overestimated their abilities and knowledge in specific areas. This overestimation arises partly because increased knowledge in a field can lead to a false sense of confidence about one's understanding and capabilities. Experts might believe they understand the nuances and intricacies of a subject better than they actually do, leading to overconfident predictions and decisions.

In conclusion, our analysis of overconfidence has so far considered a range of influential factors, including gender, age, expertise, and cultural backgrounds, each playing a distinct role in shaping this bias. These factors provide a multifaceted understanding of how overconfidence manifests in different demographics and professional contexts. Moving forward, in the subsequent sections, we will delve into a practical investigation of these theoretical insights. We plan to examine the correlation of these factors with overconfidence in a real-world setting by conducting a comprehensive questionnaire survey among managers from a selected sample.

3.3.3 Overconfidence in Capital Budgeting and Project Management

Overconfidence plays a critical role in capital budgeting, a key process in corporate finance that involves planning and management of long-term investments. The confidence level of decision-makers can significantly influence the evaluation, selection, and management of investment projects, often leading to distinctive outcomes.

One of the primary effects of overconfidence in capital budgeting is the tendency towards optimistic projections and underestimation of risks. Overconfident CEOs, for example, are more likely to overinvest, especially in internal projects and acquisitions, as they tend to overestimate returns and underestimate risks. This behavior can lead to decisions that are not optimal from a financial perspective, potentially harming the company's financial health and affecting shareholder value (Malmendier & Tate, 2005).

Additionally, overconfidence can influence the discount rates used in capital budgeting decisions. Decision-makers with overconfidence might apply lower discount rates, believing the projects to be less risky or more likely to succeed than they objectively are. This misjudgment can lead to the selection of projects that do not meet the company's required rate of return, thereby affecting long-term profitability (Ben-David, Graham, & Harvey, 2013).

Overconfident managers may also underestimate the duration and cost of projects. This underestimation can lead to significant budget overruns and project delays, impacting the overall risk profile and financial stability of the company. This aspect is particularly critical in managing expectations and resources in large-scale projects.

However, overconfidence in capital budgeting is not always detrimental. In some instances, overconfident decision-makers might champion innovative or ambitious projects that more cautious managers would avoid, potentially leading to high returns. This aspect highlights the dual nature of overconfidence in capital budgeting, acting both as a risk and a driver of innovation.

The interplay of overconfidence in capital budgeting decisions underscores the need for a balanced approach to financial decision-making. Recognizing the potential impacts of psychological biases like overconfidence is crucial for enhancing investment decisions and overall financial management within organizations.

3.3.4 Overconfidence: Escalation of Commitment

The phenomenon of escalating commitment has a substantial impact on the expenses and profitability of projects, making it a critical factor in managerial decision-making. The phenomenon of managers increasing their investment in a failing course of action is similar to the behavior observed in personal initiatives (Staw, 1976; Teger, 1980; Arkes & Blumer, 1985). Managers in corporate settings frequently demonstrate this pattern of escalation in different circumstances, such as negotiations, persisting in unsuccessful projects, and making suboptimal decisions in situations involving real options.

The tendency to disregard sunk costs can result in significant financial repercussions, as demonstrated by Ross and Staw in their analysis of the Long Island Lighting Company's Shoreham Nuclear power station. Originally estimated at $75 million, this project was eventually terminated after 23 years and a total expenditure of $5 billion. The authors credit this phenomenon to the initial overconfidence of decision-makers and a self-serving bias, whereby bad outcomes are attributed to external forces, resulting in a reluctance to alter cash flow estimates.

Furthermore, an interesting feature that remains to be thoroughly investigated in the field of behavioral corporate finance is the notion of a self-fulfilling prophecy, which arises from the optimism exhibited in project planning. Managers who establish ambitious targets and deadlines may unintentionally motivate themselves and their teams to exert greater effort in order to maximize the benefits of projects (Heath, Larrick, & Wu, 1999). This phenomenon implies that the motivation to reach or surpass high expectations might, in certain instances, foster team cohesion and contribute to progress towards such objectives, despite not ultimately achieving them.

The consequences of these actions have significant ramifications in the fields of project management and corporate finance. Managers must have a thorough understanding of the psychological foundations and the potential motivational impacts of optimistic planning. It emphasizes the importance of adopting a well-rounded approach to decision-making, which acknowledges the dangers of excessive commitment and the potential advantages of establishing ambitious yet attainable objectives. This technique requires a deep understanding of psychological biases and how they affect financial decisions. It highlights the significance of regularly evaluating and modifying project goals and investments based on changing conditions and results.

3.4 Anchoring

Anchoring, a cognitive bias first identified by Tversky and Kahneman in 1974, is a fundamental concept in understanding human decision-making. It occurs when individuals rely too heavily on an initial piece of information—the "anchor"—to make subsequent judgments. This initial anchor can significantly influence the final decision, often leading to biased outcomes. Tversky and Kahneman's groundbreaking work laid the foundation for understanding how people estimate probabilities and quantities, revealing that the initial value to which people are exposed tends to skew their final decision even if it's irrelevant to the decision at hand. Building on this, Epley and Gilovich (2001, 2005) further explored the anchoring-and-adjustment heuristic, demonstrating that while people start with an anchor and then adjust their estimates to reach a final decision, these adjustments are typically insufficient. This often results in a final estimate that remains closer to the anchor than it should be, highlighting the powerful influence of initial information on decision-making processes.

Selective accessibility, another form of anchoring, was introduced by Chapman and Johnson (1999) and further developed by Mussweiler and Strack (1997, 1999). This theory posits that when people use an anchor to make judgments, they selectively access information that is consistent with the anchor. This selective retrieval of information makes the anchor seem more relevant and appropriate, thereby strengthening its influence on the final judgment. For example, if an individual uses a high anchor to estimate a value, they are more likely to recall and consider information that supports this high estimate, ignoring other relevant information. This selective processing of information reinforces the anchor, often leading to biased and skewed decisions. This phenomenon has been observed in various contexts, from market valuations to legal judgments, indicating its widespread applicability and significance.

Englich et al. (2006) found empirical support which explains the above finding using the selective accessibility model. They demonstrated that participants who were exposed to high anchor values responded faster in categorizing incriminating arguments than those presented with low anchor values, indicating that anchor consistent information is activated by relevant anchors. These studies provide support for the argument that the anchoring effect is vulnerable to the relevance of the reference value in the task. Some research, however, has found that anchor values that are uninformative to the estimates also yield an effect on judgmental decisions. For example, Tversky and Kahneman (1974) randomly generated the anchor values by spinning a wheel of fortune. In their experiment, participants were asked to estimate the percentage of African countries in the United Nations. However, before making their estimates, they witnessed a seemingly random event: a spin of a 'wheel of fortune'. The results showed a clear anchoring effect: participants who saw higher numbers on the wheel tended to give higher estimates, and those who saw lower numbers gave lower estimates.

Attitude change is a type of anchoring that focuses on how anchors can influence people's attitudes and beliefs. Researchers like Blankenship et al. (2008) and Wegener et al. (2001, 2010) have examined how exposure to certain anchors can lead to changes in attitudes and opinions. For instance, being exposed to extreme viewpoints can serve as an anchor and shift a person's attitude in that direction, even if the shift is smaller than the extremity of the initial viewpoint. This form of anchoring demonstrates how exposure to certain information or opinions, especially those that are significantly different from a person's current beliefs, can gradually shift their attitudes. This shift is not just limited to the cognitive aspects of decision-making but extends to the affective and behavioral domains, showing how anchoring can have far-reaching implications beyond mere numerical estimates.

In summary, anchoring is a multifaceted concept with diverse applications and implications. From the basic anchoring-and-adjustment heuristic of Tversky and Kahneman to the more nuanced theories of selective accessibility and attitude change, understanding anchoring is crucial in grasping how people process information and make decisions. These theories collectively highlight the often subtle ways in which initial information can shape and bias our judgments, decisions, and attitudes, emphasizing the need for awareness and strategies to mitigate anchoring effects in various domains. In the following section, we will next explore the various factors that contribute to this cognitive bias.

3.4.1 Factors Influencing Anchoring.

Anchoring, a pivotal concept in understanding decision-making processes, is influenced by a variety of factors, each playing a significant role in how individuals assess information and arrive at conclusions. The value of the initial anchor is paramount. Studies have consistently shown that the first piece of information offered, such as a price or an estimate, strongly biases subsequent judgments and decisions. Tversky and Kahneman's groundbreaking research in the 1970s laid the foundation for understanding this phenomenon, demonstrating how even arbitrary numerical values can significantly influence estimates (Tversky & Kahneman, 1974).

Gender also plays a crucial role in the anchoring effect. Research indicates that there are gender differences in susceptibility to anchoring biases. A study by Jacquelynne Eccles and Allan Wigfield, for instance, suggested that these differences might be linked to gender-specific socialization patterns, where men and women are conditioned to process information and make decisions differently (Eccles & Wigfield, 2002). This implies that cultural and societal norms about gender can subtly influence how individuals respond to anchors.

The level of expertise and knowledge is another critical factor. While one might assume that experts are less prone to anchoring, research has shown that this is not always the case. Northcraft and Neale (1987) in their study on real estate professionals demonstrated that even experienced individuals are not immune to the effects of anchoring. However, the depth and nature of their expertise can lead to more refined adjustments from the anchor, suggesting that the relationship between expertise and anchoring is complex and context-dependent.

The perceived relevance of the anchor significantly impacts its influence. Mussweiler and Strack (2000) explored how people are more likely to be influenced by an anchor if it is seen as relevant to the task at hand. When an anchor is deemed pertinent or is presented in a context that gives it credibility, individuals are more likely to use it as a starting point in their decision-making process, often leading to a closer final judgment of the anchor.

3.4.2 Anchoring in Capital Budgeting and Project Management

The link between anchoring and capital budgeting is well-documented in financial literature, illustrating how initial estimates or figures can significantly influence investment decisions and financial projections. In the realm of capital budgeting, the initial estimates of project costs or returns often serve as anchors that can skew subsequent budgeting and investment decisions.

A notable study by Kahneman and Tversky provides the foundational understanding of how anchoring affects economic decision-making. Their work demonstrates that individuals tend to rely heavily on initial values when making estimates, a bias that can have significant implications in financial decision-making, including capital budgeting (Kahneman & Tversky, 1974). This anchoring effect means that initial cost estimates or projected returns can unduly influence the final budgeting decisions, regardless of subsequent information that might warrant a revision of these estimates.

Further research in this area, such as Bazerman's work on managerial decision-making, expands on how anchoring affects financial judgments. Bazerman highlights that in capital budgeting, managers often anchor on initial figures provided in business cases or financial projections, leading to a confirmation bias where subsequent data is interpreted in a way that supports these initial estimates (Bazerman, 2006). This can result in overconfidence in project viability and an underestimation of risks, leading to suboptimal investment decisions.

Moreover, anchoring in capital budgeting is not only limited to financial figures but also extends to project timelines and resource allocations. In real estate, for instance, Northcraft and Neale (1987) found that even expert real estate agents were influenced by the listed price of properties, an anchor, in their valuation judgments. This has parallels in project management, where initial project timelines and cost estimates can unduly influence the planning and execution phases, potentially leading to inefficient resource allocation or unrealistic scheduling.

3.5 Planning Fallacy

The planning fallacy is a cognitive bias that occurs when individuals underestimate the time, costs, and risks of future actions, while simultaneously overestimating the benefits of those same actions. This concept, extensively studied in the field of psychology and behavioral economics, has significant implications in various areas, including project management, personal planning, and policy-making.

Kahneman and Tversky (1979), who first coined the term "planning fallacy," provided the initial framework for understanding this bias. In their seminal work, they observed that people tend to be overly optimistic when estimating the time required to complete future tasks, regardless of their knowledge about similar tasks taking longer in the past. This optimism is partly attributed to a failure to consider the full range of obstacles and complications that can hinder task completion, a phenomenon linked to the broader theory of optimism bias.

Subsequent studies expanded on Kahneman and Tversky's findings. Buehler, Griffin, and Ross (1994) conducted experiments that further validated the planning fallacy, showing that most people's predictions about task completion times are not only overly optimistic but also less accurate than predictions based on historical completion times for similar tasks. They attributed this to people's focus on the best-case scenario rather than a more realistic, average-case scenario.

Another critical aspect of the planning fallacy involves the differentiation between "inside view" and "outside view" as described by Kahneman in his later work. The "inside view" is when planners make judgments based on the specifics of the project at hand, often leading to overly optimistic predictions. In contrast, the "outside view," which considers historical performance data from similar projects, tends to provide a more realistic prediction of project timelines and costs. Kahneman argued that the adoption of the outside view in planning could significantly mitigate the planning fallacy (Kahneman, 2011).

3.5.1 Factors Influencing Planning Fallacy.

In examining the factors influencing the planning fallacy, it is essential to consider various dimensions such as gender, expertise, organizational level, and socio-cultural influences. Each of these factors contributes uniquely to the propensity of individuals and groups to underestimate the time, costs, and risks of planned actions while overestimating the benefits.

Studies have shown that gender can play a role in the planning fallacy. Women are often found to be more risk-averse and may be more realistic in their time estimates compared to men. Buehler, Griffin, and Ross (1994) suggest that this difference could be due to varying risk-taking behaviors and confidence levels between genders.

Expertise in a particular field does not necessarily mitigate the planning fallacy. In fact, experts are often prone to this bias due to overconfidence in their abilities and knowledge (Kahneman & Tversky, 1979). They might underestimate the complexities or potential issues in tasks where they have proficiency, leading to optimistic time frames. The level of an individual within an organization can also influence the planning fallacy. Senior-level managers and executives might be more detached from the day-to-day realities of project execution, potentially leading to more optimistic estimates (Buehler, Messervey, & Griffin, 2005).

Cultural factors play a significant role in the planning fallacy. For instance, cultures that emphasize optimism and positive future outlooks may be more susceptible to underestimating project durations. Hofstede's cultural dimensions theory could provide insights into how national cultures impact the perception of time and risk in project planning (Hofstede, 1980).

In the following section, we will analyze other factors influencing the planning bias.

3.5.2 Other Factors Influencing The Planning Fallacy

The planning fallacy is influenced by multiple interconnected elements. Optimism bias, which refers to the inclination of individuals to have an excessively positive outlook on the success of their objectives, is a key factor influencing their behavior. Kahneman and Tversky (1979) initially discovered this bias, observing that people frequently underestimate the duration and expenses linked to tasks, influenced by an underlying optimistic perspective. The presence of this optimism bias results in distorted assessments and impractical anticipations in both personal and professional strategizing.

Another crucial aspect is the inadequate consideration of previous experiences. Although individuals may have prior experience with similar activities, they frequently struggle to effectively integrate this past data into their present planning. Buehler, Griffin, and Ross (1994) empirically proved that individuals tend to rely on idealized situations rather than realistic outcomes obtained from their previous experiences when making predictions. This lack of consideration for previous data leads to the underestimating of timelines and resources required to complete tasks.

The emphasis on the best-case scenario based on an idealized situation, disregarding more probable average or worst-case scenarios contributes to the planning fallacy. Various research investigating project planning and management have revealed that this optimistic approach to planning often results in an underestimation of the required time and resources.

A further component that worsens the planning fallacy is the excessive dependence on the 'inside perspective'. Kahneman (2011) examined the differentiation between the 'inner view' and the 'outside view' in the context of decision-making. Planners frequently prioritize the distinctive elements of the present project (the internal perspective) while disregarding statistical data from comparable previous initiatives (the external perspective). The overreliance on the internal perspective often leads to excessively optimistic project schedules and budgets, as it neglects to consider unexpected problems and obstacles that commonly develop.

Individual variations also contribute to the occurrence of the planning fallacy. Individuals' estimations of work duration and expense can be influenced by personality qualities such as overconfidence, propensity for risk-taking, and overall levels of optimism. Certain individuals may exhibit a higher susceptibility to the planning fallacy as a result of these natural characteristics, as they are more inclined to disregard potential dangers and complexities throughout their planning endeavors.

3.5.2 Planning Fallacy in Capital Budgeting and Project Management

The phenomenon of planning fallacy, extensively discussed in cognitive psychology and behavioral economics, is particularly relevant in the context of capital budgeting in corporate finance. Capital budgeting, the process of planning and managing a company's long-term investments, is often subject to the biases and heuristics that characterize individual decision-making, including the planning fallacy.

One of the key aspects of planning fallacy in capital budgeting is the tendency of managers and decision-makers to underestimate costs and overestimate the benefits of a project. This bias can lead to significant discrepancies between planned and actual performance. Flyvbjerg (2006) in his study on infrastructure projects, for instance, found substantial cost overruns and delays, largely attributable to the optimistic biases inherent in the initial planning stages. His work demonstrates how the planning fallacy can have profound implications on large-scale investment decisions, particularly where large sums of money and extensive time commitments are involved.

Kahneman and Lovallo (1993) also explored this bias in a business context, noting how the planning fallacy leads to overconfidence in financial forecasts and project outcomes. They argue that this bias is not only prevalent in individual decision-making but also manifests at the organizational level, affecting the strategic decisions of firms. The tendency to focus on best-case scenarios and disregard potential obstacles is a significant challenge in effective capital budgeting.

The implications of the planning fallacy in capital budgeting are far-reaching. Overly optimistic projections can lead to misallocation of resources, underestimation of risks, and ultimately, financial losses. This is particularly critical in capital budgeting decisions, where the stakes are high, and errors in judgment can have long-lasting impacts on a company's financial health.

To counteract the planning fallacy in capital budgeting, literature suggests incorporating more rigorous risk assessment techniques and using historical data to inform decision-making. Lovallo and Kahneman (2003) advocate for the use of the 'outside view' in forecasting and planning. By considering the statistical outcomes of similar projects, rather than relying solely on the specifics of the current project, companies can make more accurate and realistic budgeting decisions.

The planning fallacy, which significantly impacts decision-making in large-scale projects, is equally relevant in the context of managing smaller-scale projects. In these projects, despite the smaller scope and lower stakes, the same cognitive biases and tendencies can influence project managers, leading to underestimated timelines and costs, and overestimated benefits.

In small-scale project management, one of the primary manifestations of the planning fallacy is the underestimation of time and resources required for project completion. This is often due to the optimistic biases of project managers who believe that smaller projects, with seemingly fewer complexities, will be easier to control and complete. However, as demonstrated in the work of Buehler, Griffin, and Ross (1994), this optimism often overlooks unforeseen challenges and complications, leading to delays and cost overruns even in smaller projects.

The influence of the planning fallacy in smaller projects is also evident in the overconfidence of project managers regarding their control over project variables. Kahneman and Tversky's (1979) foundational work on the planning fallacy suggests that individuals, including project managers, often overestimate their ability to foresee and manage future events, a bias that can lead to overly ambitious project plans and unrealistic timelines.

Moreover, the planning fallacy in small-scale project management is often exacerbated by the lack of extensive historical data, which is typically more available in larger projects. Without a robust database of past project performances to refer to, project managers might rely more heavily on their intuition and the ‘inside view’, as described by Kahneman (2011). This reliance can lead to disregarding potential risks and challenges that are not immediately apparent during the planning phase.

To mitigate the effects of the planning fallacy in small-scale project management, the literature suggests adopting a more cautious and data-driven approach. Incorporating risk assessment techniques and learning from past similar projects, even if they are not of the same scale, can provide valuable insights. Kahneman and Lovallo (1993) advocate for the use of the 'outside view' in forecasting and planning, which involves looking at the outcomes of similar projects to make more realistic predictions, rather than relying solely on the specifics of the current project.

As we conclude our analysis of the planning fallacy in general project management, it becomes evident that this cognitive bias has far-reaching implications beyond traditional project domains. Now, we turn our attention to the realm of software project management, a field particularly susceptible to the nuances of this bias.

3.5.2 Planning Fallacies in Software Project Management

The software project manager has long been recognized as a crucial determinant of software project success. For instance, Cone (1998) shows that human turnover accounts for up to 60% of the expenses incurred in software projects. The primary cause of employees leaving a software business is their management. Weinberg (1994) synthesized the many elements of software projects and concluded that management played a more significant role in determining success than all other components together. Subsequently, Cusumano (2004) made a comparable remark, asserting that the key factor in determining success is management, rather than technology. While the available evidence supporting these claims is sparse, more recent statistics validate that the software project manager plays a more crucial role in achieving success compared to all other elements combined (Gulla, 2012). Moreno (2016) classified some software project management myths and beliefs regarding planning and scheduling.

Coming up with the right plan helps ensure success – This is a wishful thinking concept. The problem this myth creates is that it implies that once the plan has been created, the software project manager is done. However, planning and scheduling are continuous activities (Peters, 2014), and the initial plan is only the start.

If our project goes over budget or gets behind schedule early on, we can work harder and eventually finish on budget and on schedule – Based on a study of over 700 projects indicates that if the project is 15% complete and over budget, its chances of recovering and finishing within its budget are nil (Fleming, 2010). This emphasizes the need for the software project manager to closely monitor cost and schedule right from the start of the project and be willing to take remedial action if the project begins to depart from the plan and schedule.

If we had better-estimating methods, we would come closer to meeting budget requirements – It appears that regardless of our best efforts to precisely estimate any job, we are inadvertently placed at a disadvantage. Studies on human estimation have revealed that individuals tend to be excessively optimistic about their capabilities and tend to prioritize the advantages of a project's outcome to such an extent that they disregard or underestimate the associated hazards. This inherent characteristic is evident regardless of the specific approach employed (Lovallo, 2003). In recent times, a technique has emerged that allows us to mitigate the impact of excessive optimism and limit our estimation (Peters, 2015; Flyvberg, 2006). The American Planning Association strongly recommends its members always use the method known as "Reference Class Forecasting" alongside standard forecasting methods, as it has proven to be highly effective (Flyvberg, 2006). The provision includes an estimate together with a reserved amount, known as a contingency, which is determined depending on the intended level of confidence for the estimate.

In conclusion, this chapter has delved deeply into the nuances of various cognitive biases and their impact on project management and capital budgeting. Through a comprehensive analysis of the literature, we have explored the intricacies of the planning fallacy, anchoring effect, and overconfidence, understanding how these phenomena manifest in both large-scale and smaller projects. The insights gleaned from this exploration provide a solid foundation for the next phase of this study.

Moving forward, the theoretical groundwork laid in this chapter sets the stage for an empirical examination of IT projects. We will present data from a selection of IT projects, focusing on how the cognitive biases discussed have played out in real-world scenarios. This data will not only illustrate the practical implications of these biases but also offer a concrete perspective on how theoretical concepts are manifested in actual project outcomes.

Additionally, we will present the results of a questionnaire administered to project managers. This questionnaire, designed to probe the behaviors and attitudes of project managers in relation to the biases discussed, will provide valuable insights into the real-world application of these theoretical concepts. By analyzing the responses of these professionals, we aim to uncover the extent to which cognitive biases like the planning fallacy and anchoring affect decision-making in the field of project management.

Chapter 4: Empirical Analysis

4.1 Introduction

As we transition from the comprehensive literature analysis on capital budgeting and project management practices, alongside the exploration of cognitive biases like overconfidence, planning fallacy, and anchoring, we now embark on the empirical analysis chapter of this study. This chapter is dedicated to an in-depth examination of real-world case studies, provided by a renowned multinational company specializing in engineering and technology consulting, henceforth referred to as 'the Company' to maintain confidentiality in line with disclosure agreements.

The Company recognized for its expertise in various domains including banking and insurance, has generously shared data from a selection of its projects. This data comprises both development projects and software projects, offering a rich context for analysis. These projects are particularly intriguing as they include initial cost forecasts and their corresponding actual outcomes. The focus of this empirical analysis will be on dissecting these case studies to understand the real-world implications of the theoretical concepts explored earlier.

Continuing with the empirical analysis, an essential component of this study involved engaging directly with project managers from the Company. These professionals, who have hands-on experience managing the various projects under review, were invited to participate in a meticulously designed questionnaire. The aim of the questionnaire was to establish the level of overconfidence, articulated as miscalibration and better than average effect, as well as to gauge the presence of planning fallacy and anchoring biases among the respondents.

The main goal of this section is to investigate the connections between these cognitive biases and the variances found between projected and actual project costs, as well as between expected and actual profit margins. This investigation aims to highlight how cognitive biases might affect the financial performance of projects in the IT domain.

Further, this analysis intends to engage with the existing body of knowledge by examining the potential links between cognitive biases and a range of personal and professional attributes among the managerial cadre. This part of the analysis seeks to either corroborate or expand upon existing academic discussions regarding the impact of cognitive biases in professional environments, with a particular focus on project management in the rapidly evolving IT sector.

This aspect of the study is particularly crucial as it seeks to validate or challenge the theoretical connections established in the literature review. This investigation will not only enrich the understanding of cognitive biases in project management but also contribute to the broader discourse on how demographic and experiential factors shape decision-making processes in professional environments. The findings from this questionnaire are expected to offer valuable perspectives, enhancing the depth and applicability of the theoretical framework previously established.

4.2 Case Studies: Methodology and Limitations

In the methodology section of the case studies analysis, a systematic approach was employed to collect project data, ensuring the exclusion of rational factors that might otherwise skew the analysis of erroneous cost expectations. This approach encompassed several key control variables, designed to isolate the impact of cognitive biases from rational business decisions.

Firstly, the distinction between existing and new clients was considered critical. The rationale behind this control is rooted in the understanding that attracting new clients might involve strategic sacrifices in costs, potentially leading to losses. This factor was included to assess if cost underestimation was a strategic choice rather than a result of cognitive bias. However, it is important to note that all the data provided for this study pertained exclusively to existing clients of the Company (Axelssonn and Wynstra, 2002)

Secondly, the duration of the professional relationship with each client was examined. The hypothesis here is that for long-standing clients, there might be a tendency to underestimate costs in efforts to maintain these valuable relationships. This factor helps in discerning whether cost estimates were influenced by the desire to sustain client loyalty, rather than by overconfidence or planning fallacy (Muller and Judgey, 2012).

The third control variable was the degree of importance assigned to each client, rated on a scale from 1 to 5, with 1 being most important and 5 being least. The conjecture is that for clients perceived as crucial to the Company's reputation, there might be a propensity to make erroneous cost estimations. This scenario can be likened to a metaphorical example of a dog eagerly snapping at a piece of meat thrown over a cliff. While the dog secures the meat in the short term, this act leads to its eventual peril, symbolizing the short-term gains but long-term risks of underestimating costs for retaining high-value clients.

An additional control factor considered in this study is the assessment of project progress, particularly in relation to annual targets. A common concern in project management is the tendency to underestimate costs towards the end of the fiscal year, to align with predefined margin objectives. However, upon conducting brief discussions with key actors involved in these projects, an important distinction emerged. It was revealed that the project managers at the Company, who are directly involved in the day-to-day management and cost estimation of projects, do not receive direct financial incentives based on these cost decisions. Moreover, those individuals within the organization who do benefit financially from meeting margin objectives are not directly involved in making decisions about cost estimates. This separation of financial incentives from the cost estimation process is a crucial aspect, as it helps to mitigate the risk of biased cost estimations driven by personal financial gain.

Another pivotal control factor in our study is the significance of each project in achieving the Company's annual objectives. This aspect focuses on understanding how the relative importance of a project, in terms of its contribution to yearly goals, might influence cost estimations. The rationale here is that projects deemed critical for reaching annual targets may be subject to different cost estimation pressures compared to projects with less impact on these objectives. Such an analysis can reveal whether the urgency to meet annual goals leads to more conservative or aggressive cost predictions, influenced by the project's perceived importance.

Furthermore, the timing of the cost estimate, particularly the fiscal quarter in which it was made, is also examined as a control. The underlying logic here is that towards the end of the financial year, as the organization assesses its progress against pre-set targets, there might be a tendency to adjust cost estimations. Specifically, if the organization is behind its goals, there may be a propensity to overestimate costs to compensate for potential shortfalls in meeting annual objectives. Conversely, if targets are being met or exceeded, cost estimations might be more relaxed. This control aims to discern whether and how the timing of cost predictions within the fiscal year impacts their accuracy and alignment with organizational goals.

In order to categorize the projects for a more detailed analysis, a control based on the type of project was implemented. As previously mentioned, the projects provided by the Company for this study were predominantly in two categories: "software development" and "testing." Within these categories, a variety of project management methodologies were employed, with the majority following Agile principles, while others utilized the Waterfall model, and some adopted the Scrum framework. This classification is crucial as it allows for a differentiated analysis of cost estimation and project management practices based on the methodology used. The Agile methodology, known for its flexibility and iterative approach, might exhibit different patterns in cost estimation and project adaptation compared to the more structured and sequential Waterfall model. Similarly, projects following the Scrum framework, with its emphasis on regular sprints and continuous feedback, could present unique dynamics in terms of cost management and planning fallacy (Serrador and Pinto, 2015).

Another crucial control factor in this study is the type of decision-making structure within the organization. This aspect is categorized into several types: centralized, decentralized, consensus-based, democratic, and cascade decision-making.

Centralized decision-making involves key decisions being made by a small group of top-level managers or a single individual at the apex of the organizational hierarchy. This structure often leads to uniformity in decision-making but may lack the input of diverse perspectives. In contrast, decentralized decision-making is characterized by the distribution of decision-making authority across various levels or departments within the organization. This approach can enhance flexibility and responsiveness, as decisions are made closer to the operational level. Consensus-based decision-making involves seeking and incorporating input from all relevant stakeholders to reach a decision that is agreeable to all. This method fosters collaboration but can be time-consuming. Democratic decision-making is where decisions are made based on the majority vote among the members of the decision-making group. This method can promote fairness and equal participation but might overlook expert opinions. Lastly, cascade decision-making involves decisions made at higher levels being passed down through successive layers of the organization's hierarchy. This approach ensures that decisions align with the overall strategic direction but may reduce autonomy at lower levels.

Another critical control factor included in the study is the examination of the average lower and upper deviation of costs for similar projects. This control aims to understand the typical range of cost variances experienced in projects of similar nature and scope. By analyzing these deviations, the study seeks to establish benchmarks or norms for cost fluctuations in comparable project scenarios, providing a context for evaluating the accuracy of cost estimations in the current set of projects. However, it is important to note that this specific data was not available for all instances. The lack of comprehensive data on cost deviations for every project type and scenario presents a limitation in the analysis.

Finally, a key element of the data provided for this study was the detailed information on the initial cost estimates and the final actual costs of the projects, along with the delta of the final margin achieved. This data is pivotal as it allows for a direct comparison between what was projected at the outset of the projects and what was realized at their conclusion. Such a comparison is essential for empirically assessing the accuracy of cost estimations and understanding the financial implications of any deviations. However, it is important to note that the target margin data was not included in the information provided, due to disclosure restrictions. The absence of this target margin data poses a limitation to the study, as it restricts the ability to fully assess how the final margins compared to the initial financial goals set for these projects. Despite this, the available data on the estimated versus actual costs and the final margin delta still offer significant insights.

4.3 Case studies: Results

In the results section of our empirical analysis, we delve into the findings derived from three distinct datasets provided by three different teams of the company. The first dataset encompasses comprehensive data related to cost estimation and margin outcomes from various development projects. These projects, characterized by their focus on creating or enhancing products or systems, offer valuable insights into the intricacies of cost management and financial planning within the development phase.

In addition to the development project data, we were also furnished with two separate datasets pertaining to testing projects. These datasets encompass detailed information regarding cost estimations and the resultant margins from projects specifically focused on testing phases. Testing projects, being critical for ensuring product quality and reliability, present a different set of challenges and considerations in cost estimation and margin analysis compared to development projects.

The inclusion of both development and testing project datasets allows for a nuanced analysis of cost management practices across different project types within the company. By examining these datasets, we aim to uncover patterns, deviations, and insights that can enhance our understanding of the company's financial and project management strategies, particularly in relation to cost estimation accuracy and margin realization.

4.3.1 Software Developing Dataset.

We, now, focus on a series of software development projects commissioned by a banking client, which holds a high degree of importance for the company. This client has maintained a professional relationship with the company for five years, establishing a considerable history of collaborative project development. The decision-making process adopted for these projects was set within an assertive and structured framework, specifically employing a cascade decision-making method. This method is characterized by decisions being made at higher organizational levels and then flowing down through the hierarchy to the operational teams.

This structured approach to decision-making is significant in understanding the context of the cost estimation and margin results provided. The cascade method often reflects a tight alignment with strategic objectives set by senior management, which could influence project cost estimations and expectations for margins. Given the client's high importance and the established duration of the professional relationship, these factors are particularly pertinent when interpreting the cost and margin data.

Now, let’s proceed with the detailed analysis (table 1) of the provided datasets for these software development projects.

(table 1)

COST ESTIMATION STATS		DELTA MARGIN STATS	
AVERAGE	-27,11254505%	**AVERAGE**	-2,89%
DEV.ST.P	48,4285531	DEV.ST.P	0,484285531
VARIANCE	2345,324755	VARIANCE	0,234532476
AVERAGE 1st quarter	84,91507692%	**AVERAGE 1st quarter**	-114,92%
DEV.ST.P	0	DEV.ST.P	0
VARIANCE	0	Var	0
AVERAGE 2nd quarter	-27,89046546%	**AVERAGE 2nd quarter**	-2,11%
DEV.ST.P	3,709532968	DEV.ST.P	0,03709533
VARIANCE	13,76063484	VARIANCE	0,001376063
AVERAGE 3rd quarter	-9,436475998%	**AVERAGE 3rd quarter**	-24,51%
DEV.ST.P	57,90457269	DEV.ST.P	0,656617963
VARIANCE	3352,939538	VARIANCE	0,43114715
AVERAGE 4th quarter	-81,181555%	**AVERAGE 4th quarter**	51,18%
DEV.ST.P	12,11745244	DEV.ST.P	0,121174524
VARIANCE	146,8326536	VARIANCE	0,014683265

Cost Estimation Stats:

- Overall: The average of -27.11 across all quarters indicates that the actual costs incurred were lower than initially estimated. This suggests that the projects overall were managed more cost-effectively than expected.
- 1st quarter: The data shows a positive average of 84.92, which stands out as an outlier, indicating that costs in this period were notably higher than anticipated.
- 2nd quarter: The average is -27.89, which follows the overall trend of actual costs being lower than estimated.
- 3rd quarter: Here we see an average of -9.44, suggesting a smaller discrepancy between estimated and actual costs.
- 4th quarter: The average significantly drops to -81.18, pointing to a substantial underestimation of costs for this period.

Delta Margin Stats:

- Overall: The overall expected delta margin is -2.89%, implying a slight overall decrease in profitability compared to what was projected.
- 1st quarter: There's a remarkable negative delta margin of -114.92%, indicating a significant shortfall in profitability.

- 2nd quarter: The delta margin is -2.11%, which is slightly below expectations, maintaining the general trend.
- 3rd quarter: A more substantial negative delta margin of -24.51% is observed, suggesting a notable difference between expected and actual profitability.
- 4th quarter: In contrast, there is a positive delta margin of 51.18%, indicating that the actual profitability far exceeded expectations for this timeframe.

It is crucial to acknowledge the limitations presented by the variability in the data, as indicated by the standard error and variance values. While these statistics do provide a measure of the spread of the data, they also suggest that the precision of the cost estimates and margin predictions varied. This variability, particularly in the 2nd and 4th quarters, may affect the interpretation of the trends and the reliability of the results and should be considered when drawing conclusions from this data.

Moreover, the dataset did not include information on the advancement of project objectives. Such data would typically enable us to assess whether projects were meeting their scheduled milestones and progressing as planned, which can significantly influence cost estimations and margin results. The lack of this information prevents us from examining the potential impact of project progress on financial outcomes.

Additionally, the dataset did not provide details on the influence of each project in terms of its contribution to overall annual targets. Understanding the relative importance of individual projects could have helped us to better evaluate whether the financial performance of each was in line with its significance to the company's broader strategic goals.

Furthermore, average discrepancies for similar types of projects were not included. This comparative data could have been instrumental in establishing benchmarks or norms for cost fluctuations and margin expectations, providing a context for evaluating the accuracy of cost estimations in the current set of projects.

In the forthcoming sections, we undertake a comprehensive examination of both rational and behavioral explanations to elucidate why, despite the costs being lower than anticipated, the margins remained negative.

4.3.1.1 Rational Explanations for Lower-than-expected Margins

Several rational explanations, beyond behavioral biases, could account for the negative delta margins observed despite actual costs being lower than expected:

Revenue Shortfalls

A possible reason for the negative delta margins could be a lack of revenue. Even if a project is completed with lower actual costs than first estimated, the expected profit margins can still be adversely affected if the realized revenue is lower than anticipated. This disparity may arise owing to several market-related issues, including diminished product demand, unforeseen changes in customer tastes, or the failure to attain the projected sales price due to competitive market forces.

Fixed Costs Allocation

Assigning fixed costs in project accounting can also lead to negative delta margins. Fixed costs, which remain constant regardless of the level of production, may have been allocated according to the initial cost projections. If the fixed costs stay the same despite the reduction in project expenses, the savings from decreased variable costs may not result in greater profit margins as anticipated.

Quality and Rework

Another element to consider is the increased expenditures that may emerge from quality control concerns or necessary rework. If the initial cost estimates failed to sufficiently consider these prospective expenses, then even if the development phase is completed with lower costs than anticipated, the additional expenses incurred to remedy these quality concerns could offset the savings, negatively impacting the project's profit margins.

Contractual Penalties

Contractual penalties for failing to fulfill specific project benchmarks or deadlines can have a substantial impact on the reduction of profit margins. If the project, even though it was completed within the allocated budget, faced penalties due to delays or failure to meet specified contract requirements, these penalties could significantly reduce the anticipated profits, resulting in a negative difference.

Competitive Bidding

Competitive bidding refers to a process in which multiple parties submit their offers or proposals to compete for a certain project, contract, or opportunity. Competitive bidding tactics may have altered the initial project cost estimation. To ensure the contract, the company may have submitted a bid with narrow profit margins. Consequently, despite the project costs being lower than anticipated, there may be little opportunity for profit enhancement due to the assertive original price strategy. This occurrence is frequently observed in areas such as banking, where securing a contract from a reputable client can be very competitive.

4.3.1.2 Behavioral Explanations for Lower-than-expected Margins

In addition to logical explanations for the negative delta margins, behavioral aspects could offer valuable insights into the reasons behind the lower-than-expected profits, despite costs being within the budget.

Overconfidence

Overconfidence in software development projects may have caused project managers to create overly positive revenue predictions or underestimate possible difficulties. This cognitive bias can lead to a conviction that the project will outperform others or that one possesses the ability to exert control or accurately forecast project outcomes beyond what is truly feasible. Overconfidence can result in establishing excessively optimistic profit objectives that fail to materialize when confronted with the practicalities of project implementation and market circumstances.

Anchoring

Anchoring may have taken place if the initial cost calculations or revenue projections were derived from historical data or preliminary information that did not fully capture the current project difficulties or market trends. The subsequent estimations and choices may have been unduly impacted by these reference points, resulting in misaligned projections for the project's financial success.

Planning fallacy

The occurrence of the planning fallacy may have played a role in the underestimation of the required time or resources for the effective completion of the project, despite the reduced expenses. This cognitive bias causes individuals to rely on optimistic possibilities when making predictions, disregarding the possibility of obstacles or unexpected challenges. Hence, despite the project costs being lower than expected, the overall profit margin could still suffer due to unanticipated delays or other expenses that were not initially considered.

Confirmation bias

Confirmation bias may have also influenced the cascading decision-making process. Higher-level decision-makers may have engaged in confirmation bias by selectively collecting or favoring information that supported their preexisting opinions or conclusions regarding the project's profitability while dismissing data that indicated a requirement for more cautious margin estimations. This bias can contribute to a loop in which only corroborating evidence is considered, resulting in an overestimation of margins despite potential cost savings.

These behavioral explanations propose that cognitive biases can have a substantial influence on the financial administration of projects, potentially resulting in discrepancies between projected and realized profit margins.

4.3.2 1st Software Testing Dataset

In analyzing the first set of data related to software testing, we are looking at a diverse clientele of the company, with the specific industries of these clients not being disclosed. These clients vary in their levels of importance to the company, which may influence the prioritization, allocated resources, and strategic approach to their projects.

This dataset presents an opportunity to gain insights into the variations in cost estimation and profit margins across different software development techniques and decision-making models used within the company. Since clients are considered with varying degrees of importance, this could potentially affect the cost-benefit analysis and the urgency with which projects are pursued and managed.

By scrutinizing the cost estimations and margin outcomes of software testing projects, we can begin to draw comparisons between the effectiveness of Agile, Scrum, and Waterfall methodologies in this particular domain. Additionally, the dataset may reveal how centralized, decentralized, democratic, and consensus-based decision-making models impact the financial metrics of these projects.

Let's start the analysis by examining the general averages from the case studies provided. The data presented (table 2) here encompasses various metrics pertinent to software testing projects from clients of varying degrees of importance to the company.

(table 2)

COST ESTIMATION STATS		DELTA MARGIN STATS		PAST DISCREPANCIES	
AVERAGE	-25,83333333%	**AVERAGE**	38,13%	**AVERAGE**	-14,29%
DEV.ST.P	35,30620027	DEV.ST.P	0,136787929	DEV.ST.P	0,104978132
VARIANCE	1246,527778	VARIANCE	0,018710938	VARIANCE	0,011020408

The negative figures in the cost estimation statistics indicate that actual costs were, on average, lower than expected, sitting at an average of -25.83. This suggests that, generally, the projects were managed cost-effectively, with actual expenditures being less than what was budgeted or anticipated.

The delta margin stats show a 38.13% average, which represents a substantial positive discrepancy between the expected and actual profit margins. This indicates that, on average, the projects achieved higher profitability than planned, which could be a result of the effective cost management indicated by the cost estimation stats or other factors such as higher-than-expected revenues.

Additionally, the columns labeled "PAST DISCREPANCIES" refer to the averages provided in relation to past discrepancies in cost estimation. The figure of -14.29% for the past discrepancy suggests that there has been a history of projects where the cost estimations were positively exceeded, meaning the actual costs were even lower than the past estimates, reinforcing the trend of conservative budgeting practices or efficiency in project execution.

Client importance data analysis

(table 3)

COST ESTIMATION STATS		DELTA MARGIN STATS		PAST DISCREPANCIES	
AVERAGE Grade 1 Client	-21,111%	**AVERAGE Grade 1 Client**	37,50%	**AVERAGE Grade 1 Client**	-15,00%
DEV.ST.P	39,553838	DEV.ST.P	0,1547848	DEV.ST.P	0,111803399
VARIANCE	1564,506173	VARIANCE	0,0239583	VARIANCE	0,0125
AVERAGE Grade 2 Client	-45%	**AVERAGE Grade 2 Client**	45%	**AVERAGE Grade 2 Client**	N/A
DEV.ST.P	0	DEV.ST.P	0	DEV.ST.P	N/A
VARIANCE	0	VARIANCE	0	VARIANCE	N/A
AVERAGE Grade 3 Client	-35%	**AVERAGE Grade 3 Client**	35%	**AVERAGE Grade 3 Client**	-25%
DEV.ST.P	0	DEV.ST.P	0	DEV.ST.P	0
VARIANCE	0	VARIANCE	0	VARIANCE	0

Based on the data (table 3) provided by the Company, here's a comparative analysis of the cost estimation and margin statistics relative to client importance:

Clients of Grade 1, considered the most important, show lower actual costs than estimated with an average of -21.11 and a high delta margin of 37.50%, indicating efficient cost management and profitability. Grade 2 clients exhibit a greater negative average of -45 in cost estimation, suggesting significantly lower actual costs than estimated compared to Grade 1, and the highest observed delta margin at 45.00%, indicating very profitable outcomes. For Grade 3 clients, the average of -35 and a delta margin of 35.00% suggest that while the cost management is better than expected, the profitability is less than that seen with Grade 2 clients but on par with Grade 1 clients. Historical data indicates that Grade 1 clients have experienced past cost discrepancies of -15.00%, while Grade 3 clients have seen even higher past discrepancies at -25%.

We encounter notable limitations that must be acknowledged. A critical constraint is the absence of adequate data for clients of Grades 2 and 3. With only a single data point provided for each of these client categories, it is challenging to draw statistically significant conclusions or to identify clear trends regarding the impact of client importance. This scarcity of data is reflected in the absence of standard error and variance values for these grades, which are essential metrics for assessing the reliability and consistency of the observed figures.

Without a range of data points for Grades 2 and 3 clients, any variance or standard error calculations would be undefined or zero, which falsely implies precision and fails to capture the true variability in cost and margin estimations. Therefore, while the available data for Grade 1 clients allows for some initial observations, this data insufficiency hinders our ability to perform a robust comparative analysis and truly understand how the company's financial management might differ with the level of client importance.

Type of software developing techniques data analysis.

(table 4)

COST ESTIMATION STATS		DELTA MARGIN STATS		PAST DISCREPANCIES	
AVERAGE Agile	-50%	**AVERAGE Agile**	47,50%	**AVERAGE Agile**	-8,75%
DEV.ST.P	12,74754878	DEV.ST.P	0,090138782	DEV.ST.P	0,021650635
VARIANCE	162,5	VARIANCE	0,008125	VARIANCE	0,00046875
AVERAGE Waterfall	6,111111%	**AVERAGE Waterfall**	33,33%	**AVERAGE Waterfall**	N/A
DEV.ST.P	36,166624	DEV.ST.P	0,084983659	DEV.ST.P	N/A
VARIANCE	1308,024691	VARIANCE	0,007222222	VARIANCE	N/A
AVERAGE Scrum	-25	**AVERAGE Scrum**	15,00%	**AVERAGE Scrum**	-5%
DEV.ST.P	0	DEV.ST.P	0	DEV.ST.P	0
VARIANCE	0	VARIANCE	0	VARIANCE	0

We can make the following comparative analysis (table 4) regarding Agile, Waterfall, and Scrum methodologies:

Agile methodology shows an average of -50, indicating that costs were significantly less than expected. This underestimation is paired with a high delta margin of 47.50%, suggesting that Agile projects are yielding considerable profitability. The past positive discrepancy of 8.75% for Agile indicates that the current underestimation of costs and overperformance in margins align with the historical average, although the current margin outperformance is notably higher than the past average.

With an average of -25, Scrum projects also cost less than expected, though not to the same degree as Agile. The delta margin for Scrum is 15.00%, which is the lowest among the three methodologies but still indicates profitability. The past positive discrepancy for Scrum is 5%, suggesting that while Scrum projects have historically seen cost underestimation, it is not as pronounced as the current data suggests.

The average for Waterfall is 6.11, which uniquely indicates that costs were slightly overestimated, a contrast to the underestimation seen in Agile. Despite this, the projects still exhibit a healthy delta margin of 33.33%, which is impressive but not as high as Agile and Scrum. The absence of past discrepancy data for Waterfall means we cannot determine if this overestimation is an outlier or in line with past trends.

The analysis is limited by data scarcity, particularly the lack of multiple data points for Scrum (as indicated by a standard error of 0), which means we are drawing conclusions from a single project rather than a trend. There is no past discrepancy data for Waterfall, which hinders our ability to compare current performance against historical averages and understand the typical financial performance of Waterfall projects. The absence of a standard error and variance for Waterfall and Scrum in the delta margin stats also limits the analysis. Without these, we cannot accurately assess the consistency of the margin performance across different projects within these methodologies.

In summary, while Agile, and its subset technique Scrum, appear to be the best-performing methodologies in terms of cost management and profitability according to this dataset, the limited data points for Waterfall and Scrum make it difficult to draw firm conclusions about their comparative performance. A more robust dataset would be needed to confirm these findings and to understand the broader implications for project management practices within the company. Regarding these limitations later in this chapter we will make some considerations about these differences.

Decision-making technique data analysis.

(table 5)

COST ESTIMATION STATS		DELTA MARGIN STATS		PAST DISCREPANCIES	
AVERAGE Consensus-Based Decisions	-50%	**AVERAGE Consensus-Based Decisions**	47%	**AVERAGE Consensus-Based Decisions**	8,75%
DEV.ST.P	12,74754878	DEV.ST.P	0,090138782	DEV.ST.P	0,021650635
VARIANCE	162,5	VARIANCE	0,008125	VARIANCE	0,00046875
AVERAGE Cascade Decisions	30%	**AVERAGE Cascade Decisions**	30%	**AVERAGE Cascade Decisions**	35%
DEV.ST.P	0	DEV.ST.P	0	DEV.ST.P	0
VARIANCE	0	VARIANCE	0	VARIANCE	0

AVERAGE Decentralized Decisions	-35%	**AVERAGE Decentralized Decisions**	30,00 %	**AVERAGE Decentralized Decisions**	-5%
DEV.ST.P	10	DEV.ST.P =	0,15	DEV.ST.P	0
VARIANCE	0	VARIANCE	0,0225	VARIANCE	0
AVERAGE Democratic Decisions	33,3333 3333%	**AVERAGE Democratic Decisions**	25,00 %	**AVERAGE Democratic Decisions**	25%
DEV.ST.P =	0	DEV.ST.P =	0	DEV.ST.P =	0
VARIANCE =	0	VARIANCE =	0	VARIANCE	0

From the dataset provided (table 5), a comparative analysis of different decision-making types shows various impacts on cost estimation and margin outcomes in software testing projects:

- Consensus-Based Decisions: Projects managed with consensus-based decision-making show an average of -50, indicating that actual costs were significantly lower than expected. This suggests a conservative approach to cost estimation or high efficiency in project execution. The delta margin for consensus-based decisions is 47.50%, indicating that the profit margins were considerably higher than anticipated. With a past positive discrepancy of 8.75%, it appears that the current performance is consistent with the historical trend of positive outcomes for consensus-based decisions, although the present margin performance is notably better.
- Cascade Decisions: For projects with cascade decision-making, there's an average of 30, which uniquely indicates that costs were overestimated, leading to actual costs being lower than expected. This contrasts sharply with the consensus-based approach. The delta margin is at 30.00%, which is positive but lower compared to consensus-based decisions. The past discrepancy is -35.00%, suggesting that the current performance is a significant improvement over past performance, which historically saw negative discrepancies.
- Decentralized Decisions: With decentralized decision-making, the average of -35 shows that actual costs were less than expected. The delta margin is at 30.00%, reflecting profitability, although not as high as consensus-based decisions. The past discrepancy of -5.00% indicates a history of slight positive discrepancies, suggesting that the current performance is an improvement.
- Democratic Decisions: Democratic decision-making has an average of 33.33, meaning actual costs were higher than expected, which differs from the other decision-making types. The delta margin is the lowest at 25.00%, indicating lower profitability, and the past negative discrepancy of -25.00% is in line with this trend, suggesting consistently lower performance historically.

Overall, while consensus-based decisions appear to yield better outcomes for cost estimation and profitability, the limited dataset cautions against drawing definitive conclusions. A broader dataset with multiple data points for each decision-making type would provide a more comprehensive understanding of their relative effectiveness in software testing projects.

In the following sections, we will explore some rational explanations for these differences in cost estimation between different decision-making models. But firstly, we will make some consideration about the discrepancies in cost estimation among the software developing models we analyzed through these datasets.

4.3.2.1 Why Agile and Scrum Outperform Waterfall: a Rational Explanation.

In discussing why Agile and Scrum methodologies outperform Waterfall in terms of cost estimation and profit margins, we can draw upon various non-behavioral, rational explanations supported by academic literature.

Agile's Flexibility and Adaptability

Agile methodology is designed to be adaptive and responsive to change, which is a crucial advantage in the dynamic environment of software development. This flexibility allows for continuous reevaluation and adjustment of project trajectories, which can lead to more accurate cost estimations as the project evolves. The iterative nature of Agile can also contribute to earlier detection of potential cost overruns, enabling corrective actions that safeguard profit margins. (Highsmith, 2009)

Scrum's Incremental Delivery

Scrum's emphasis on short sprints and incremental delivery means that costs can be closely monitored and controlled throughout the development process. This continuous scrutiny often results in a tighter alignment between estimated and actual costs. Moreover, Scrum's frequent iterations provide regular opportunities to re-assess and optimize the allocation of resources, contributing to efficient cost management and the potential for higher margins. (Schwaber & Sutherland, 2013)

Waterfall's Sequential Nature

The sequential phase-based structure of the Waterfall model can be a disadvantage when it comes to cost estimation and margins. Once a phase is completed, it is generally not revisited, which means that any inaccuracies or issues in the cost estimates from earlier phases can cascade and amplify through the project's lifecycle, making it difficult to correct course once the project is underway. This can lead to less accurate cost estimations and potentially lower profit margins. (Royce, 1970)

In the subsequent section, we will delve into the behavioral explanations that account for Agile and Scrum methodologies outperforming Waterfall in terms of cost estimation and profit margins. This analysis will explore the psychological and cognitive factors influencing project management approaches and decision-making processes.

4.3.2.2 Why Agile and Scrum Outperform Waterfall: a Behavioral Explanation.

Agile and Scrum approaches have the potential to surpass Waterfall in terms of cost estimation and profit margins due to many behavioral factors associated with human cognition and group dynamics.

Overconfidence

Overconfidence can arise from Waterfall's linear and phased strategy, as it may foster excessive assurance in the planning and execution process. Project managers may develop a lot of trust in their estimations and the improbability of modifications, as a result of the meticulous upfront planning that the Waterfall methodology necessitates. This excessive self-assurance can lead to a failure to sufficiently consider uncertainties and potential hazards, resulting in increased expenses and diminished profits.

Anchoring

In Waterfall projects, the initial cost and time estimates frequently function as fixed reference points. As the project advances through its stages, any deviations can be significantly influenced by these original reference points, even if fresh evidence indicates that changes are needed. The iterative procedures of Agile and Scrum enable re-estimation and adaption as the project progresses, hence preventing the risks associated with being anchored to obsolete assumptions.

The planning fallacy, a cognitive bias in which individuals tend to underestimate the time, costs, and hazards associated with future actions while overestimating the rewards, is especially common in the Waterfall project management approach due to its strong focus on early project planning. Agile and Scrum approaches, known for their adaptability and iterative approach, help mitigate the planning fallacy by integrating continuous learning and feedback. This enables more precise estimations and planning.

Group Dynamics

Group dynamics are enhanced by Agile and Scrum methodologies, which promote improved collaboration and communication through frequent meetings, retrospectives, and reviews. These approaches promote ongoing communication and feedback, enabling teams to discover and resolve difficulties compared to the sequential approach of Waterfall, which often isolates stages promptly and efficiently.

These behavioral explanations indicate that Agile and Scrum, due to their flexibility, adaptability, and iterative character, are more suitable for managing biases and cognitive fallacies that can negatively impact project outcomes. This leads to more precise cost estimations and enhanced profit margins.

Before we proceed to dissect the rational and irrational factors contributing to the apparent superiority of the consensus-based decision-making model, it is essential to turn our attention to the third dataset. This dataset is expected to provide further empirical insights into the outcomes associated with different decision-making models.

4.3.2 2nd Software Testing Dataset.

Now, we focus on a specific dataset concerning the management team of the company that operates within the insurance sector. This team is engaged with a Grade 2 client — a client of considerable but not paramount importance to the company — with whom there exists a substantial eight-year working relationship. Such a duration signifies a deep familiarity and a potentially well-established workflow and rapport between the company and the client.

As we embark on this analysis, we acknowledge upfront some limitations that frame the context of our dataset. Notably, all case studies within this dataset pertain to projects executed in the fourth quarter. This temporal limitation could introduce seasonality factors that might not be representative of other quarters. Additionally, the dataset encompasses a relatively small number of projects, which restricts the breadth of our analysis and may limit the generalizability of our findings.

However, despite these constraints, the dataset holds particular value as all decisions across these projects were made using a democratic decision-making model. This uniformity in approach allows us to continue building upon our understanding of this model's influence on project outcomes. These insights will contribute to a richer comprehension of how collective decision-making impacts project management, cost estimation, and margin realization within a sector known for its complexity and regulatory demands.

(table 6)

COST ESTIMATION STATS		DELTA MARGIN STATS	
AVERAGE	12,25%	**AVERAGE**	-12,25%
DEV.ST.P	0,110085194	DEV.ST.P	0,110085194
VARIANCE	0,01211875	VARIANCE	0,01211875

The dataset presented (table 6) shows an average of 12.25% for cost estimation stats, indicating that the actual costs were higher than anticipated. This overestimation of costs signifies that the project may have encountered unforeseen expenses or that the initial budgeting was not as accurate as needed.

In terms of the delta margin stats, the average is -12.25%, revealing that the profit margins were lower than projected. This discrepancy in margin could be due to the higher actual costs incurred or a shortfall in revenue, possibly a combination of both factors.

The standard error (DEV.ST.P) is given as 0.110085194 for both cost estimation and delta margin stats, which points to some variability around the mean, although it is not excessively high. The variance at 0.01211875 for both metrics also suggests a modest spread in the data.

As we interpret these figures, it is crucial to consider the limitations of the dataset as noted in the introduction. The data represents projects from only the fourth quarter, which may not capture the full annual cycle and could be affected by end-of-year financial practices or seasonal market trends. Moreover, the sample size is small, which could limit the generalizability of these results.

Nevertheless, these preliminary insights from the second and third datasets provide valuable indicators that can inform future project management strategies and decision-making processes. They suggest a potential correlation between decision-making models and project financial performance. In the following sections, we will analyze some rational and irrational factors that determine the best performance of some decision-making models with respect to others.

Nevertheless, these preliminary insights from the second and third datasets provide valuable indicators that can inform future project management strategies and decision-making processes. They suggest a potential correlation between decision-making models and project financial performance. To further investigate this relationship, all the data received from the company were consolidated, and a regression analysis was conducted. This analysis aimed to delve deeper into the dynamics between decision-making processes and their impact on financial outcomes in projects. The findings and implications of this regression analysis will be discussed in detail in the forthcoming section, shedding light on how these variables interact and influence each other in the context of project management.

The regression analysis conducted focused on cost deviation as the dependent variable (Y), with three independent variables (X) representing different decision-making models: hierarchical decisions, consensus-based decisions (unanimity), and decentralized decisions. Dummy variables were employed, set to 1 when cost deviations were associated with these decision-making methods and 0 otherwise. Notably, democratic decision-making was excluded from the model as an independent variable, serving as the baseline for comparison. Therefore, a negative beta coefficient for any of the included decision-making models indicates that, relative to democratic decision-making, these methods are associated with less favorable outcomes in terms of cost deviation.

4.3.2.1 Exploring the Relationship: Decision-Making Impact on Project Success

The regression analysis conducted focused on cost deviation as the dependent variable (Y), with three independent variables (X) representing different decision-making models: cascade decisions, consensus-based decisions (unanimity), and decentralized decisions. Dummy variables were employed, set to 1 when cost deviations were associated with these decision-making methods and 0 otherwise. Notably, democratic decision-making was excluded from the model as an independent variable, serving as the baseline for comparison. Therefore, a negative beta coefficient for any of the included decision-making models indicates that, relative to democratic decision-making, these methods are associated with less favorable outcomes in terms of cost deviation. The results are the following:

```
(table 7)
Residuals:
    Min       1Q   Median       3Q      Max
-120.796 -12.1364   0.0000  12.1364 120.796

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
Cascade_Decisions            -37.2338    21.30943  -1.7472  0.099749.
Consensus_Decisions          -66.466     25.62833  -2.5934  0.019599 *
Decentralized_Decisions      -51.466     31.96414  -1.6101  0.126922

Residual standard error: 38.20446 on 16 degrees of freedom
Multiple R-squared:  0.313646,    Adjusted R-squared:  0.184954
F-statistic: 2.5488 on 3 and 16 DF,  p-value: 0.092305
```

$$\textbf{Cost Discrepancy} = -37.2338 \times \textbf{Cascade Decisions} + (-66.466)\ \textbf{Consensus Decisions} + \varepsilon$$

The regression analysis (table 7) presents a nuanced view of the relationship between various decision-making models and cost deviations. With an obtained p-value of 0.092305 for the overall model, the results approach the conventional threshold for statistical significance, which suggests a moderately significant fit of the model to the observed data.

The coefficient estimates for the decision-making variables, when compared to the baseline category of democratic decisions, indicate their respective associations with cost deviations. Notably, the model suggests that consensus-based decisions are linked to a reduction in costs, as evidenced by the negative coefficient of -66.466, which is significant at the $p < 0.05$ level. This finding implies that when consensus-based decisions are employed, costs are lower than expected, which can be interpreted as a favorable outcome.

The coefficients for cascade decisions and decentralized decisions also show negative values, -37.2338 and -51.466, respectively. While these coefficients suggest that these decision-making methods are associated with reduced costs when they are the primary strategy, their p-values do not fall below the conventional threshold for statistical significance ($p < 0.05$). However, given the p-values are relatively close to this threshold, there is an indication that these decision-making styles may also contribute to cost efficiencies, albeit with less certainty than consensus-based decisions.

It is important to highlight that the negative sign of the coefficients for all decision-making variables in the model indicates that these approaches are associated with lower-than-expected costs. This is an advantageous finding as it suggests potential cost-saving benefits of these decision-making models in project management contexts.

In summary, the regression analysis indicates that there is a meaningful relationship between decision-making models and cost deviations in projects. Consensus-based decisions stand out as a statistically significant predictor of cost efficiency. While hierarchical and decentralized decisions also show a negative relationship with cost deviations, suggesting a similar direction of effect, these findings are not statistically significant at the 5% level and thus warrant cautious interpretation. The overall model's p-value further suggests that while the predictors collectively explain a reasonable proportion of variance in cost deviations, further research with a larger sample size may be necessary to confirm these preliminary findings.

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In light of the regression analysis findings suggesting that certain decision-making models may lead to cost efficiencies, the forthcoming sections of our study will delve into a deeper exploration of the underlying mechanisms. We will analyze both rational and irrational reasons that could elucidate why democratic decision-making practices appear to outperform other methods in terms of cost management. This exploration aims to uncover the cognitive and behavioral factors that might influence the effectiveness of decision-making processes within organizational and project management contexts

4.3.2.2 Rational Explanations for Decision-making Model Efficacies

When exploring the reasons why decision-making models such as consensus-based and decentralized approaches may be more effective than democratic and cascade models in project management, a thorough analysis of the literature reveals logical justifications.

Consensus-based decision-making is distinguished by its collaborative essence, wherein feedback is solicited from all team members prior to arriving at a decision. The utilization of this model can result in more comprehensive and rigorously evaluated conclusions, as it integrates a range of viewpoints and specialized knowledge. This is particularly crucial in intricate domains like software development (Vroom & Jago, 1988). Furthermore, when team members perceive that their viewpoints are highly regarded, it can result in increased acceptance and dedication to project objectives, hence boosting motivation and productivity (Cotton & Jennings, 1988). Incorporating inclusion can mitigate the possibility of overlooking potential hazards and cultivate inventive resolutions to challenges, ultimately resulting in more precise cost projections and enhanced profit margins.

Decentralized decision-making models assign authority to individuals or teams who are near the relevant tasks or processes. The proximity between decision-makers generally leads to expedited decision-making and problem-solving processes, as those involved possess a more comprehensive comprehension of the pertinent matters. The flexibility provided by this paradigm can be especially impactful in fast-paced workplaces where quick adaptations to change are required, therefore improving project efficiency and financial results.

Conversely, democratic decision-making, although inclusive, can occasionally result in delayed decision-making due to the requirement of achieving a majority consensus. Within project environments that need timely execution, this might lead to setbacks and escalated expenses (Hastie & Kameda, 2005). Cascade decision-making, characterized by a hierarchical flow of decisions, may encounter a disconnection between decision-makers and implementers. This division can result in a dearth of pragmatic understanding in decision-making, potentially leading to suboptimal decisions and an inability to effectively adapt to on-the-ground circumstances.

These logical arguments indicate that the success of a decision-making model in project management relies on its capacity to utilize collective expertise, adapt quickly to changing conditions, and match decision-making authority with practical insights. Although consensus-based and decentralized models have their merits, it is crucial to consider the specific circumstances and needs of the project when determining the most appropriate decision-making method.

4.3.3.2 Irrational Explanations for Decision-making Model Efficacies

Exploring the irrational factors that can explain the different effectiveness of decision-making models, we come across a range of cognitive biases that influence organizational decision-making processes.

Overconfidence is a cognitive bias that can significantly impact the cascade model, which involves decision-making at upper levels that subsequently propagate downstream. Leaders may possess an inflated perception of their competence and fail to accurately assess hazards, resulting in excessively positive cost predictions or unduly ambitious project timeframes. This cognitive bias can lead to decisions that do not adequately consider the intricacy of activities or possible impediments, frequently resulting in increased costs and decreased profit margins (Moore & Healy, 2008).

The anchoring effect is an additional irrational component that has the potential to influence decision-making. Within democratic models, the initial information or viewpoint expressed by a vocal member of a group can have a disproportionate influence on the decisions made by the rest of the group. This influence remains significant even when additional information indicates an alternative course of action (Tversky & Kahneman, 1974). This might result in a continued commitment to less-than-ideal tactics or budget estimates, even when faced with conflicting data.

The planning fallacy is a prevalent cognitive bias in project management, characterized by decision-makers consistently underestimating the time, resources, or prices required to effectively finish a project. This fallacy can be present in all decision-making frameworks, but it is especially pronounced in environments that prioritize speedy consensus or authoritative conclusions above comprehensive analysis. The inclination to strategize based on ideal circumstances can result in a systematic underestimation of possible obstacles, frequently resulting in failure to meet deadlines and excessive expenditures (Buehler, Griffin, & Ross, 1994).

These cognitive biases highlight the irrational factors that might influence decision-making in companies. The consequences mentioned can be alleviated by employing consensus-based and decentralized models. These models distribute decision-making authority and incorporate many opinions, thereby acting as a safeguard against individual biases. Nevertheless, no model is impervious to these psychological inclinations, and their influence can be detected throughout the range of decision-making procedures in project management.

As we conclude our exploration of the various decision-making models and their impacts on project management, we now prepare to shift our focus toward a more introspective analysis. Up next, we will examine a survey administered to the managers within the company, designed to measure their susceptibility to anchoring, overconfidence, and the planning fallacy. This survey will serve as a tool to assess the degree to which these cognitive biases are present among the decision-makers and could potentially explain the observed discrepancies in profit margins within the first dataset. Additionally, it will offer insights into whether these irrational tendencies might account for the differential results witnessed across different software development techniques and the decision-making models applied.

4.4 Questionnaire: Methodology and Limitations

The research design centers around a carefully structured questionnaire aimed at capturing a comprehensive profile of project managers, as well as a control group comprising software testers and developers. The objective of this questionnaire is twofold: firstly, to gather demographic and professional background information about the respondents, and secondly, to evaluate their psychological predispositions in terms of risk aversion, susceptibility to planning fallacy and anchoring, degree of miscalibration (overconfidence), and the propensity towards a better-than-average effect.

The questionnaire is divided into distinct parts, with the initial section dedicated to collecting baseline information about the respondents. This demographic data is crucial as it enables the identification of patterns or correlations between the respondents' backgrounds and their cognitive biases. The initial part of the questionnaire includes the following information:

Age: Understanding the age distribution of respondents helps to assess whether experience correlates with cognitive biases.

Gender: This demographic variable is collected to examine any potential gender-related differences in cognitive bias or risk aversion.

Instruction: The respondents' level of education is recorded to determine if there's a link between educational background and susceptibility to the biases in question.

Experience in the Field: The number of years the respondents have been working in their respective fields is queried to evaluate the relationship between industry experience and cognitive bias.

Experience in "The Company": Specifically, the duration of employment within the current company is noted to explore if familiarity with company processes affects bias.

Working Field: The particular domain or field in which the respondents are working, such as the banking industry, IT, the insurance industry, automotive, rail industry, renewable energy, healthcare, and defense.

Job Position: The role or position held by the respondent within the organization is recorded to assess if hierarchical status influences cognitive biases.

Following this section, project managers were presented with two distinct self-assessment scales:

Technical Self-Evaluation: This part of the questionnaire asked project managers to rate their own technical expertise. The options provided were designed to capture a range of self-perceived proficiency levels, from "very low" to "very high". This self-rating helps to identify how project managers view their own technical abilities in relation to the demands of their job roles and responsibilities.

Relationship Quality Self-Evaluation: The second scale focused on the project managers' assessment of the quality of their relationships with their colleagues, clients, and other stakeholders. The same five-point scale ranging from "very low" to "very high" was used to measure perceived interpersonal effectiveness. High-quality relationships can be indicative of strong communication skills, empathy, leadership, and conflict resolution abilities—all of which are instrumental in navigating the complex social dynamics of project teams and client interactions.

The subsequent section of the survey delves into evaluating the level of risk aversion among project managers, a trait that significantly influences management style and decision-making. Understanding an individual's risk profile is particularly important in project management, where decisions often involve weighing potential risks against expected benefits.

The survey instrument includes a series of questions designed to gauge respondents' risk preferences. Each question presents a scenario with varying degrees of risk and uncertainty, asking respondents to choose between options that reflect different risk-taking behaviors. To quantify the level of risk aversion, a scoring system is employed where each response is assigned a specific number of points.

These points reflect the degree of risk associated with the choice — with lower points allocated to risk-averse selections and higher points to risk-seeking ones.

The following block of questions in the survey is structured to assess the project managers' propensity for poor planning — a critical aspect that can have substantial implications for project success. This section aims to identify the presence and extent of the planning fallacy among the respondents, which is the tendency to underestimate the time, resources, or costs necessary to complete a project successfully, leading to underplanning, or to overestimate these aspects, leading to overplanning.

Nine carefully crafted questions probe into various planning scenarios, challenging respondents to predict outcomes based on their judgment and experience. Each question is designed to reflect common situations where planning fallacies might occur.

The scoring system for this section assigns points to each response based on the direction and magnitude of the planning bias: negative points are allocated to answers that suggest underplanning, indicative of a respondent underestimating the required resources or timeframes; Positive points are given to answers that imply overplanning, where a respondent might overallocate resources or overestimate the time needed for project tasks.

By totaling the points from all planning-related questions, the survey generates a planning bias score for each respondent. A negative aggregate score indicates a general tendency toward underplanning, while a positive score points to a tendency toward overplanning.

The subsequent portion of the survey delves into examining the influence of anchoring on decision-making among the participants. In this section, participants were presented with a scenario designed to assess their susceptibility to anchoring effects. To add depth to the analysis, the participants were divided into two groups: one group received the scenario with a relevant anchor, while the other group received the same scenario but with both a relevant anchor and an irrelevant one.

The sequent section of the survey targets the concept of miscalibration, specifically focusing on overconfidence among participants. Miscalibration in this context refers to the discrepancy between individuals' confidence in their knowledge and the actual accuracy of their responses. Overconfidence is a common form of miscalibration where individuals believe their knowledge or predictions are more accurate than they truly are.

In this part of the survey, participants were asked a series of general knowledge questions. For each question, they were required not only to provide an answer but also to define a range (minimum and maximum values) within which they were 90% confident their answer fell. This approach was designed to assess the breadth of their confidence intervals in relation to their actual knowledge.

The level of overconfidence was quantified by analyzing the proportion of questions for which the actual answer fell outside the participant's 90% confidence interval. If a participant correctly included the actual answer within their confidence interval for 5 out of 10 questions, their overconfidence level would be calculated as 40%. This figure is derived from the expectation—based on their 90% confidence level—that the correct answer would lie within their provided range for 9 out of 10 questions, whereas it only did so for 5 questions.

The following section of the survey addresses the "better than average" effect, a cognitive bias where individuals assess their abilities to be above the average, irrespective of reality. This effect is particularly relevant in project management, where an inflated self-assessment can lead to unrealistic project commitments and expectations.

Participants were presented with a scenario, they were then asked to place themselves in a percentile rank compared to their peers based on their performance in these scenarios. The 50th percentile represents the median, implying an average performance level among peers.

Each deviation above the 50th percentile was analyzed as an indication of the better-than-average effect. This approach allows for a quantitative assessment of how pronounced this bias is among project managers and the control group. By aggregating these deviations, the survey aims to measure the extent to which individuals overestimate their competencies and skills.

Following the data collection phase, the subsequent step involved a comprehensive analysis of the gathered information. This analysis encompassed examining the means, minimums, maximums, and correlations among the results to glean valuable insights. Subsequently, the datasets from the case studies were amalgamated with the findings in an effort to identify potential correlations using Pearson's correlation coefficient. Additionally, various regression analyses were conducted to explore relationships within the data. This methodical approach facilitated a deeper understanding of the underlying patterns and relationships.

However, it's important to acknowledge the limitations encountered during the analysis. Many of the data points did not achieve statistical significance, as evidenced by Pearson's correlation and the t-value test. Similarly, the Mann-Whitney U test, used to assess differences between groups, also did not yield statistically significant results in many instances. Despite these challenges, some statistically significant insights were uncovered and will be discussed further. These findings provide valuable contributions to the research, despite the limitations posed by the non-significant results in certain areas of the study.

To enhance the quality of future data and potentially yield more statistically significant results, it is recommended that the company increase the number of participants in future studies. Additionally, obtaining more detailed information on the case study data could prove beneficial. These steps would likely contribute to a more robust dataset, enabling more conclusive analysis and insights.

The complete questionnaire is the following:

Personal information

Age:

- Less than 25 years

- 26-35 years

- 36-45 years

- 46-55 years

- More than 55 years

Gender:

- Male

- Female

- Other

- Prefer not to say

Level of Education:

- High school diploma

- Bachelor's degree (3-year degree)

- Master's degree

- Doctorate

- Other

Years of Work Experience in the Field:

- Less than 1 year

- 1-3 years

- 4-6 years

- 7-10 years

- More than 10 years

Years of Work Experience at the Company:

- Less than 1 year

- 1-3 years

- 4-6 years

- 7-10 years

- More than 10 years

Current Main Work Area:

- Aerospace Engineering

- Automotive

- Railways

- Renewable Energy and Environment

- Telecommunications and IT

- Life Sciences and Healthcare

- Banking Sector

- Defense and Security

- Insurance Sector

- Other

Current Position within the Company:

- Junior Manager

- Manager

- Senior Manager

- Project Director

- Other

Technical Skills in Project Management:

- Very low

- Low

- Medium

- High

- Very high

Interpersonal Skills as a Manager:

- Very low

- Low

- Medium

- High

- Very high

Risk Aversion (The points assigned to each answer, indicated in parentheses, reflect the respondent's risk orientation: lower scores suggest a propensity for risk aversion, whereas higher scores suggest a propensity for risk-seeking behavior)

When faced with an important decision, which approach do you prefer to take?

- I carefully analyze all available data and information. (-1 risk aversion point)

- I rely on my intuition and past experiences. (1 risk aversion point)

- I seek a balance between detailed analysis and intuition. (0 risk aversion point)

- I prefer to delegate the decision to someone more experienced. (-2 risk aversion points)

How do you react to a project with a high potential for gain but also a high risk of loss?

- I avoid it, preferring safer options. (-2 risk aversion point)

- I carefully evaluate it and decide based on my risk tolerance. (1 risk aversion point)

- I am inclined to accept the risk for the high potential gain. (2 risk aversion points)

- I seek multiple opinions before making a decision. (0 risk aversion points)

When managing a project, how do you balance risk and innovation?

- I prioritize safety and minimize risks. (-1 risk aversion point)

- I seek a balance between safety and innovation. (0 risk aversion points)

- I am inclined to take risks if it leads to significant innovations. (1 risk aversion point)

- Innovation is always my priority, even at the expense of potential risks. (2 risk aversion points)

In a situation of uncertainty, how do you manage pressure?

- I prefer to avoid uncertain situations.

- I assess the risks and opportunities before acting.

- I feel comfortable making decisions in uncertain situations.

- I actively seek out uncertain situations for the opportunities they may offer.

Which statement best describes your approach to failure management?

- Failure is unacceptable and must be avoided at all costs. (-1 risk aversion point)

- Failure is unpleasant but can be a learning opportunity. (1 risk aversion point)

- I am open to failure as part of the learning and growth process. (2 risk aversion points)

- Failure does not concern me; it is a necessary step towards success. (3 risk aversion points)

Planning fallacy (The points assigned to each answer indicated, in parentheses, reflect the respondent's propensity to planning fallacy)

Thinking about the last month, how did you manage your expenses compared to what you had planned at the beginning of the month?

- Much less than expected expenses: I spent much less than I had planned at the beginning of the month. (- 2 risk aversion points)

- Slightly less than expected expenses: I spent slightly less than I had planned at the beginning of the month. (-1 risk aversion point)

- Exactly as expected: I spent exactly the amount I had planned at the beginning of the month. (0 risk aversion points)

- Slightly more than expected expenses: I spent slightly more than I had planned at the beginning of the month. (1 risk aversion points)

- Much more than expected expenses: I spent much more than I had planned at the beginning of the month. (2 risk aversion points)

When you plan a meeting, how often do you arrive earlier or later than expected?

- Always less than expected (I always arrive early) (- 2 risk aversion points)

- Usually less than expected (I often arrive early) (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Usually more than expected (I often arrive late) (1 risk aversion point)

- Always more than expected (I always arrive late) (2 risk aversion points)

When grocery shopping, how often do you spend more or less than the budget you set for yourself?

- Always less than the budgeted amount (- 2 risk aversion points)

- Usually less than the budgeted amount (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Usually more than the budgeted amount (1 risk aversion point)

- Always more than the budgeted amount

When you go on vacation, how often do you spend more or less than the travel budget you had planned?

- Always less than the budgeted amount (- 2 risk aversion points)

- Usually less than the budgeted amount (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Usually more than the budgeted amount (1 risk aversion point)

- Always more than the budgeted amount (2 risk aversion points)

When you start a project or task, how often do you complete it in more or less time than planned?

- Always less time than expected (- 2 risk aversion points)

- Usually, less time than expected (-1 risk aversion point)

- Exactly as expected

- Usually more time than expected (1 risk aversion point)

- Always more time than expected (2 risk aversion points)

When preparing a meal, how often do you take more or less time than expected between preparation and cooking?

- Always less time than expected (- 2 risk aversion points)

- Usually, less time than expected (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Usually more time than expected (1 risk aversion point)

- Always more time than expected (2 risk aversion points)

When you start studying for an exam, how much time do you expect it to take to prepare adequately?

- Much less time than expected (- 2 risk aversion points)

- Slightly less time than expected (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Slightly more time than expected (1 risk aversion point)

- Much more time than expected (2 risk aversion points)

When organizing an event or a party, how often is the final cost more or less than the budgeted amount?

- Always less than the budgeted amount (- 2 risk aversion points)

- Usually less than the budgeted amount (-1 risk aversion point)

- Exactly as expected (0 risk aversion points)

- Usually more than the budgeted amount (1 risk aversion point)

- Always more than the budgeted amount (2 risk aversion points)

When planning activities for the weekend, how often do you manage to do more or less than you had planned?

- Always less than planned (2 risk aversion points)

- Usually less than planned (1 risk aversion points)

- Exactly as expected (0 risk aversion points)

- Usually more than planned (-1 risk aversion point)

- Always more than planned (-2 risk aversion points)

Anchoring with both relevant and irrelevant anchors

You represent a company that manufactures and sells automobile parts. Unexpectedly, a Japanese company requests a component that you produce. Fortunately, you have enough pieces to fulfill the Japanese company's request. The price at which you sell the piece is €20. The cost of the piece is €10, so any price above this is pure profit. Given the timing, the Japanese company has few alternatives and is highly motivated to buy. *In an initial meeting with the Japanese company, the translator, who is not an expert and difficult to understand, seems to indicate that the price they would accept is €32* ***(irrelevant anchor)***. Upon requesting clarification, the translator tells you that you misunderstood and that they never provided an opinion on the price. Subsequently, they ask you to provide your proposal.

Please indicate the price you would propose:

Please indicate the minimum price that would satisfy you:

Please indicate the absolute minimum price you would be willing to accept:

Anchoring with only relevant anchors

You represent a company that specializes in the production and sale of automobile parts. Unexpectedly, a Japanese company has requested a component that you produce. Fortunately, you have enough pieces to meet the Japanese company's request. The price at which you sell the part is €20. The cost of the part is €10, so any price above this is pure profit. Given the timing, the Japanese company has few alternatives and is highly motivated to purchase.

Please indicate the price you would propose:

Please indicate the minimum price that would satisfy you:

Please indicate the absolute minimum price you would be willing to accept:

Miscalibration

We ask you to spontaneously answer each question by providing a minimum and maximum value within which you believe the correct answer to the question lies, with 90 percent certainty. The range you choose can be as broad as you like.

- Age of Martin Luther King when he died
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Length of the Po River (in Km)
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Diameter of the Moon (in Km)
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Weight of a Boeing 747 without passengers (in Kg)

- Minimum: [Your Answer]
- Maximum: [Your Answer]

- Number of participants at "The Last Supper" by Leonardo da Vinci
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Number of Member States of the United Nations
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Year of birth of Wolfgang Amadeus Mozart
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Gestation period of an Asian elephant (in days)
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Aerial distance from Rome to Paris (in Km)
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]
- Total number of players on the field during an ice hockey game
  - Minimum: [Your Answer]
  - Maximum: [Your Answer]

Better than average effect

Imagine being involved in a group project with 100 other people who share your age, experience, and work background. Before the start of this project, you learn that the person who contributed the most positively will receive a significant promotion. Estimate the percentile in the sample (from 1 to 100) that you think represents your position in obtaining the promotion.

PS: A percentile is a measure that indicates a person's position within a group. Imagine the group as a line ordered from the lowest to the highest performance. The percentile tells you at which point in that line you stand.

[Your Answer]

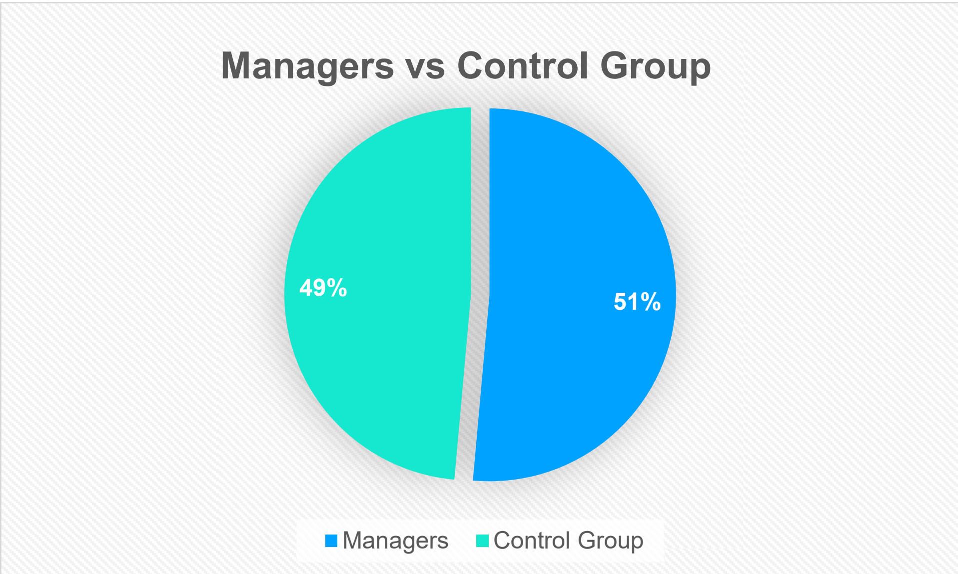
The subsequent section will focus on the description of the sample. This will involve a detailed exploration of the demographic and professional characteristics of the participants, providing a contextual backdrop against which the findings of the current analysis can be further understood and appreciated.

4.4.1 Profile of Survey Respondents: An Overview

This section will outline the demographic and professional attributes of the participants, such as age range, gender distribution, professional background, years of experience, and other relevant characteristics that may offer insights into the decision-making trends observed. Graphical representations will be a pivotal part of this analysis, offering an immediate visual understanding of the population's composition.

Managers vs Control Group

(figure 1)

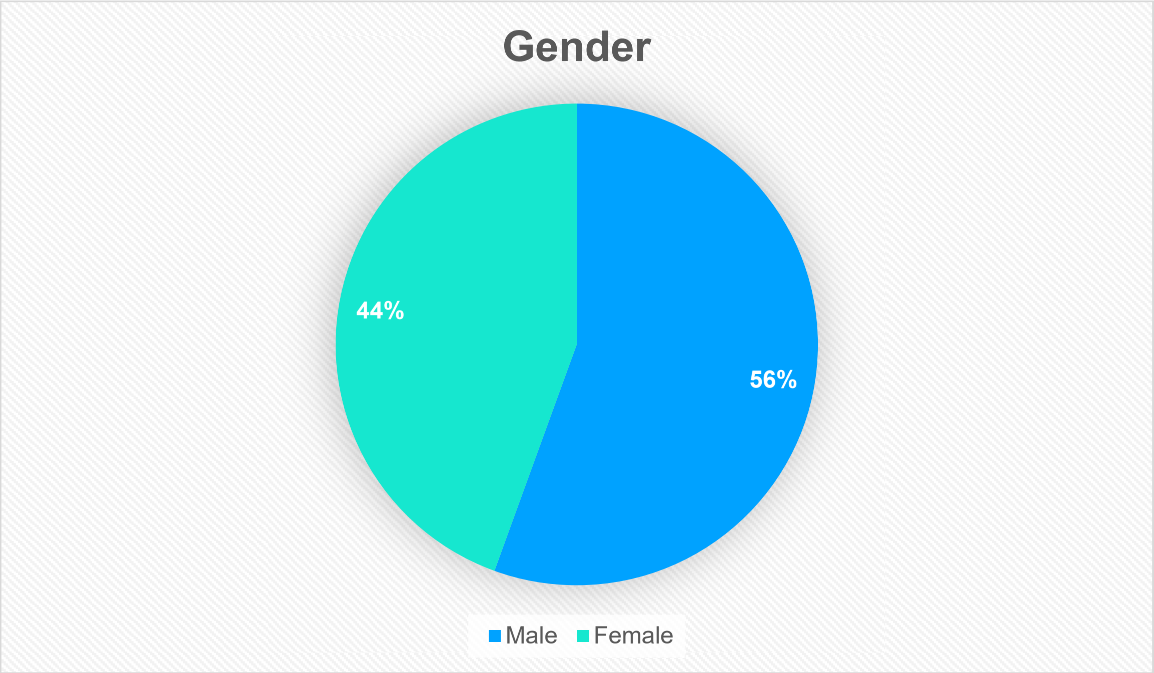


The population under investigation in this study comprises a targeted selection of professionals from within the company, encompassing two distinct groups (figure 1). The first group consists of 18 managers who play a pivotal role in steering the strategic direction and making critical decisions within the organization. The second group serves as a control and includes 17 individuals from the company's technical staff, specifically testers and software developers, whose day-to-day functions are more execution-focused rather than strategic.

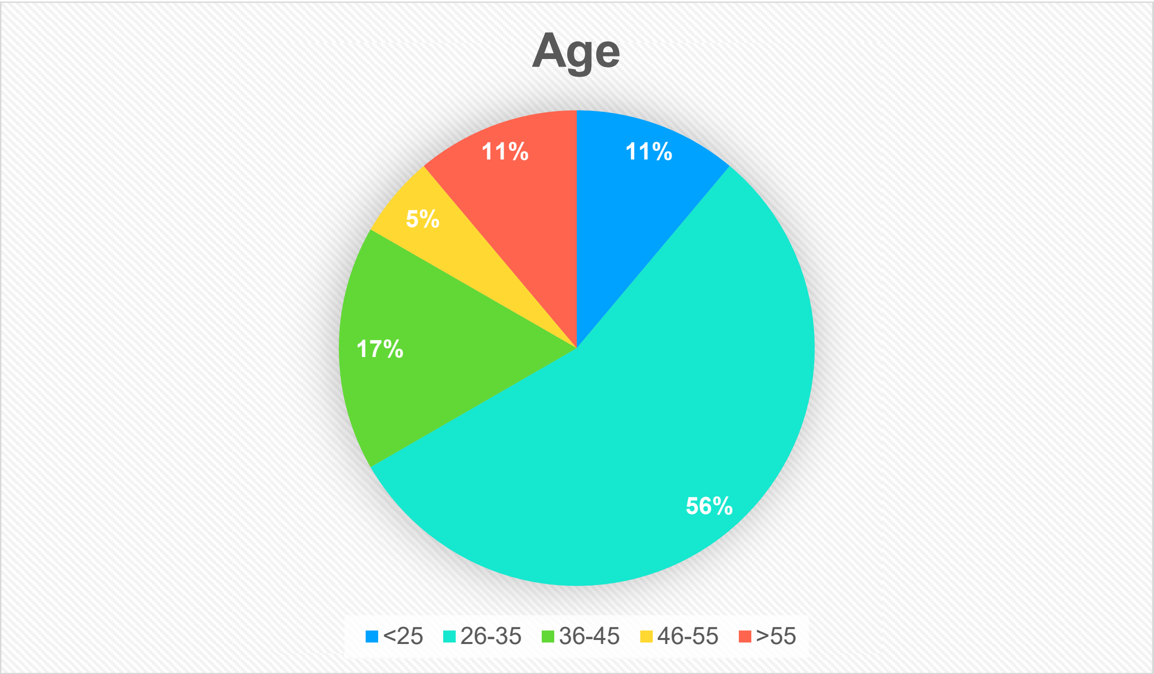
In the forthcoming analysis, we will turn our focus specifically to the population of managers, delving into their demographic and professional backgrounds. This detailed examination will encompass various critical factors including age, gender, industry experience, level of education, and tenure within the company.

Managers population: Gender and Age

(figure 2)



(figure 3)



In the manager cohort surveyed for this study, there is a balanced representation of genders, with 10 of the participants identifying as male and 8 identifying as female (figure 2). This near parity in gender distribution provides a unique opportunity to explore potential differences in decision-making styles, risk assessment, and susceptibility to behavioral biases between male and female managers within the company.

The survey results show (figure 3) that the majority of managers surveyed are between the ages of 26 and 35, with a total of 10 managers falling within this age range. These findings indicate that the group consists of relatively young professionals, with a notable proportion of persons who are likely in the early to mid stages of their managerial careers.

There is a low representation of persons in both the younger and older age ranges. The poll comprises two managers who are below the age of 25, implying the existence of youthful professionals in managerial positions. This could indicate a rapid advancement in their careers or the promotion of exceptionally talented individuals into management at an early stage.

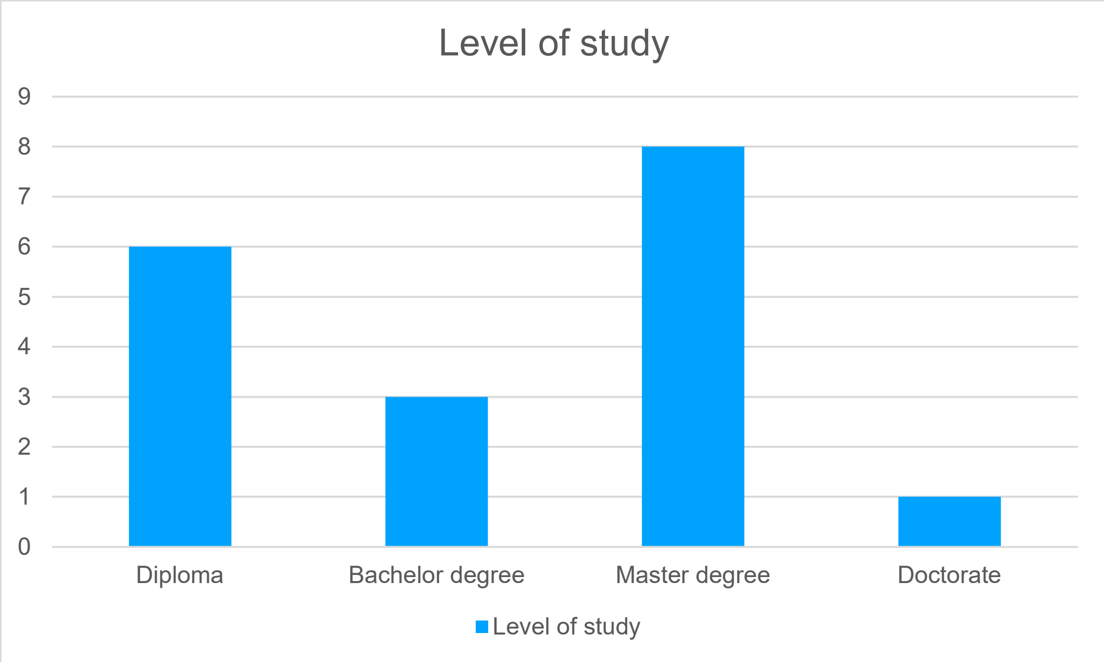
Within the age group of 36-45, there are a total of 3 managers. This indicates the presence of individuals in the middle stage of their careers who have likely gained substantial expertise. As a result, it is reasonable to anticipate that these managers will exhibit a combination of enthusiasm and experience while making decisions.

There is only one manager in the age group of 46-55, indicating a limited presence of experienced professionals in the later stages of their careers who may possess valuable expertise and potentially adopt a more cautious management style.

Lastly, the survey indicates that 2 managers are over the age of 55, providing the potential for insights from seasoned professionals who have likely witnessed a broad span of industry changes and may offer a depth of knowledge in their decision-making.

In general, this age distribution encompasses a wide variety of viewpoints, ranging from the innovative and potentially more willing risk methods of younger managers to the experienced, potentially more cautious techniques of older managers.

Managers: Educational level and experience



(figure 4)

(figure 5)

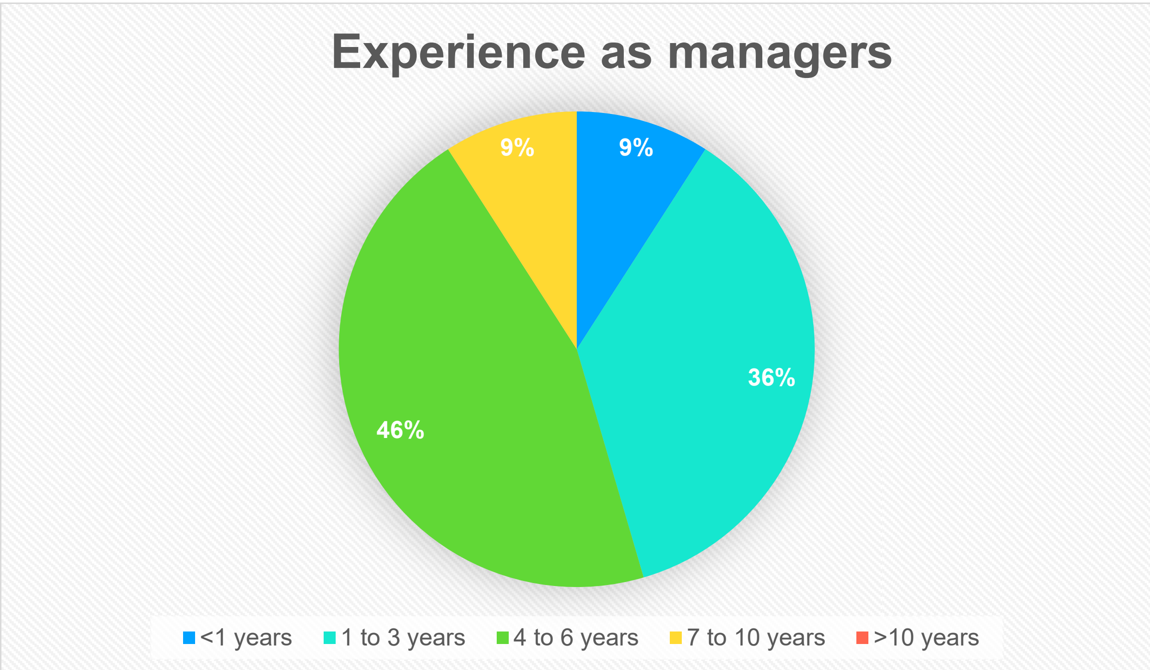
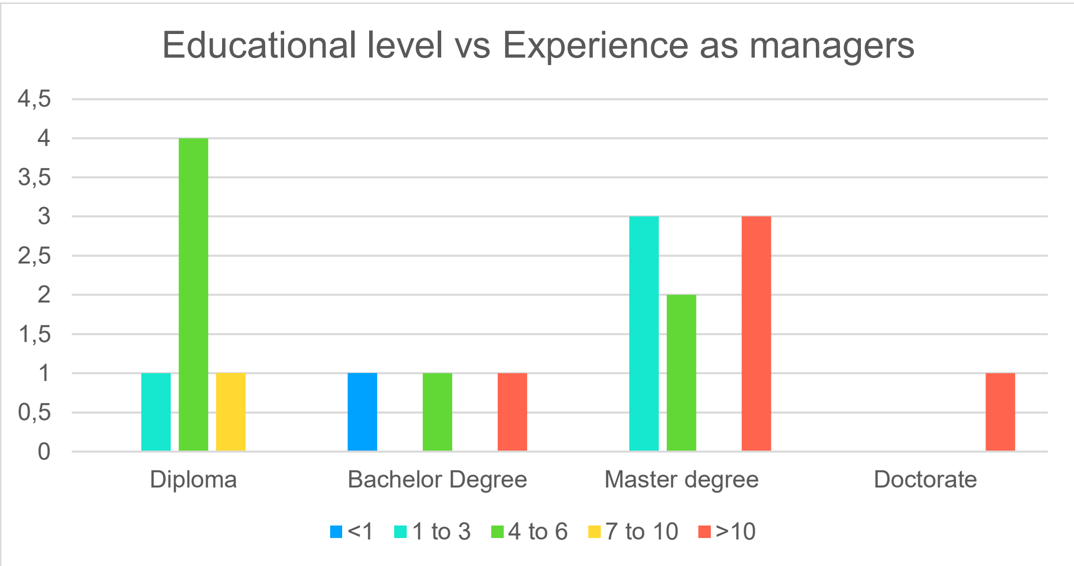


Figure 4 illustrates the educational attainment levels of the manager cohort. The majority of managers, eight in total, have obtained a Master's degree, indicating a strong representation of advanced academic achievement within the group. This level of education often involves specialized knowledge and analytical skills, which can be expected to influence their decision-making processes and potentially their awareness of and susceptibility to cognitive biases.

Following closely, hold a Diploma, suggesting that a significant segment of the management has professional qualifications that may not necessarily be academic in nature but are likely specialized in their respective fields

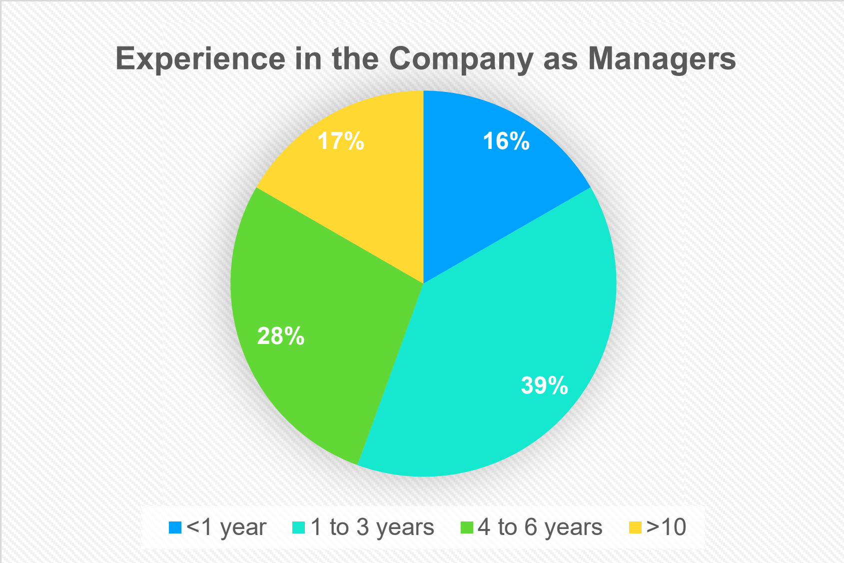
Three managers have a Bachelor's degree, indicating they have completed undergraduate-level education, which provides a broad foundation of knowledge and critical thinking skills that are essential in managerial roles.

Lastly, there is one individual with a Doctorate, signifying the highest level of academic achievement within the group. A Doctorate degree often indicates not only a deep expertise in a particular field but also extensive experience in research and critical analysis, which can significantly impact managerial decisions and strategic thinking.



The data (figure 6) illustrates a diverse range of managerial experience within the company, spread across various educational backgrounds. Managers with a Diploma are predominantly found within the mid-experience range of 4 to 6 years but also show a presence across the experience spectrum from less than a year to over a decade. Bachelor's degree holders are evenly distributed, with representation among those new to management, those with several years of experience, and those with extensive experience exceeding ten years. Master's degree holders show a bifurcation in experience; a notable number are either relatively new to their managerial roles or have accumulated a wealth of over ten years of experience. There is a single Doctorate holder who brings to the table more than ten years of management experience. This spread suggests that while higher education levels might fast-track individuals into management roles, extensive managerial experience is not exclusive to those with advanced degrees. Overall, the company's management exhibits a rich tapestry of educational qualifications intersecting with varied lengths of managerial tenure.

Managers: Years of experience in the Company and managerial position

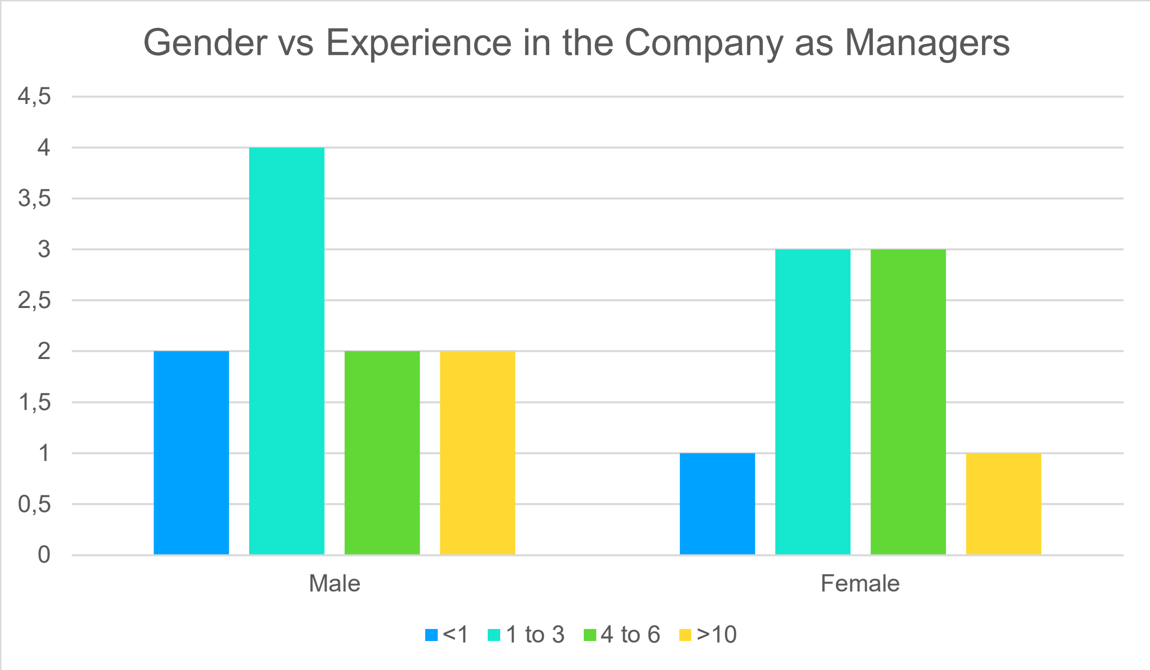


(figure 7)

The distribution of managerial experience (figure 7) within the company shows a concentration of individuals in the early to mid-range of their careers, with the largest group, seven managers, having 1 to 3 years of experience. This is followed by five managers with a tenure of 4 to 6 years, suggesting a solid middle cohort with moderate experience. Both the <1 year and >10 years categories have the lowest representation, with three managers each, indicating fewer managers at the extremes of either being very new to their roles or being highly seasoned.

Figure 8 (below) provides a clear depiction of the company's gender distribution across different levels of managerial experience. From the sample, it can be inferred that the company fosters career advancement with relative equality between male and female managers. Both genders are represented across all tenure brackets, from less than one year to over ten years of experience. This suggests that the company's career development opportunities are similarly accessible to both men and women, contributing to a balanced professional growth environment.

(figure 8)



In the upcoming sections, we will delve into the analysis of data pertaining to biases and compare them with the dataset of case studies, utilizing statistical values and employing regressions.

4.4.2 Overconfidence: Miscalibration Results

In this section, we delve into the evaluation of overconfidence among the participants, which was assessed based on their responses to a series of 10 general knowledge questions. Participants were instructed to provide a minimum and maximum range within which they were 90% confident the correct answer fell. The calculation of overconfidence was derived from the deviation between the participants' stated confidence intervals and the actual correctness of their responses.

For instance, if a participant correctly answered 5 out of the 10 questions, their level of overconfidence would be calculated as 90% (their stated confidence level) minus 50% (the actual correctness rate), resulting in a 40% overconfidence level.

After calculating the overconfidence levels of the survey participants, the next step involved examining potential differences between the control group and the managers using the Wilcoxon rank-sum test. Subsequently, several correlations suggested by the literature were explored, including gender, age, and experience. Additionally, correlations with cost deviations and expected margins provided by the company were investigated. To maintain confidentiality and ensure accurate analysis, unique codes were assigned to each group of project managers, enabling the identification of their respective datasets.

Among the 18 interviewed project managers, 15 were included in the subsequent analysis. The average cost deviation for Group A was calculated at -12%, and this value was associated with the overconfidence scores of the individual group members. Similar associations were conducted for the other groups.

By examining the relationship between overconfidence and cost deviation, we aim to determine if there is a significant association between these variables. Understanding this relationship can provide valuable insights into the decision-making processes of project managers and their potential impact on project outcomes.

Next, we will present the results of these analyses, including any significant findings, correlations, and their implications for understanding the behavior of project managers within the company.

4.4.2.1 Managers vs Control Group

(table 8)

MANAGERS MISCALIBRATION	
AVG TOT	50,55555556
MIN	0
MAX	80
DEV.ST	22,22917
CONTROL GROUP MISCALIBRATION	
AVG TOT	40,625
MIN	0,00
MAX	70
DEV.ST	18,18954026
WILCOXON TEST	
W	103.5
P-VALUE	0.1604

Table 8 contains statistics that compare the level of miscalibration between managers and a control group. The average total miscalibration for the managers is approximately 50.56, with scores ranging from 0 (the minimum, indicating no miscalibration) to 80 (the maximum, indicating a high degree of overestimation). The standard deviation for this group is about 22.23, which points to a relatively wide dispersion of miscalibration scores among the managers.

In contrast, the control group shows a lower average miscalibration of 40.63, with their scores also starting at 0 (no miscalibration) and peaking at 70, which is somewhat lower than the managers' maximum score. The standard deviation for the control group is approximately 18.19, indicating a slightly narrower range of scores compared to the managers, but still a considerable spread.

To determine if the differences observed in miscalibration between the two groups are statistically significant, a Wilcoxon test was conducted. The Wilcoxon test is a non-parametric statistical test that compares two paired groups. It is used when the data does not necessarily come from a normal distribution, making it a suitable choice for this analysis. The test calculates a "W" statistic, which in this case is 103.5, and provides a p-value to determine the significance of the results. The p-value is a measure of the probability that the observed results could have occurred under the null hypothesis, which in this context posits that there is no real difference in miscalibration between the two groups.

With a p-value of 0.1604, the result is not considered statistically significant, as it is above the conventional threshold of 0.05. This indicates that the differences in miscalibration between the managers and the control group, as observed in this sample, could very well be due to chance. Therefore, based on this analysis, there is not enough evidence to assert that the levels of miscalibration differ significantly between the two groups being studied.

4.4.2.2 Managers Miscalibration: Gender

(table 9)

AVERAGE MALE	48
MIN	0
MAX	70
DEV.ST	24,41311
AVERAGE FEMALE	51,42857
MIN	20
MAX	80
DEV.ST	18,84415
WILCOXON TEST P-VALUE	0.7126

In Table 9, the average score for the male group stands at 48, with individual scores ranging from zero, indicating no presence of the measured trait or behavior, to a high of 70, showcasing a considerable spread among individual scores as evidenced by the standard deviation of approximately 24.41. This variability points to diverse outcomes or behaviors within this group.

Contrastingly, the female group's average score is slightly elevated at approximately 51.43. The range of scores for females starts at 20, eliminating the lowest scores seen in the male group, and peaks at 80, which is higher than the maximum score observed for males. The standard deviation for females is about 18.84, indicating a narrower distribution of scores, which implies that female scores are more consistently clustered around the mean than those for males.

A Wilcoxon test was applied to these data, yielding a p-value of 0.7126. This high p-value suggests that the differences in average scores between the male and female groups are not statistically significant. In other words, any observed difference in the average scores of males and females in this sample could likely be attributed to random chance rather than a systematic difference between the two groups.

In addition to the Wilcoxon test, a correlation analysis was conducted between gender (categorized as 1 for males and 2 for females) and the scores, revealing a correlation coefficient of 0.13. This positive correlation coefficient indicates a slight tendency for females to be more associated with the measured trait, potentially overconfidence, than males. However, the strength of this relationship is very weak given the proximity of the correlation coefficient to zero.

The T-value associated with this correlation is 0.50, which is quite low. In hypothesis testing, a higher T-value typically indicates a stronger divergence from the null hypothesis, which in correlation testing is that there is no association between the variables. A T-value of 0.50 suggests that the correlation coefficient of 0.13 is not statistically significant since it does not exceed the critical value required to reject the null hypothesis for a given confidence level. Therefore, despite the slight positive correlation indicating that women might be marginally more correlated with overconfidence, we cannot consider this finding conclusive or indicative of a real difference in overconfidence between the genders, according to the sample data provided.

4.4.2.3 Managers Miscalibration: Age

(table 10)

MISCALIBRATION: AGE	
AVERAGE <25	45
MIN	40
MAX	50
DEV.ST	5
AVERAGE 26-35	51
MIN	0
MAX	80
DEV.ST	25,47547841
AVERAGE 36-45	60
MIN	40
MAX	70
DEV.ST	14,14213562
AVERAGE 46-55	20
MIN	0
MAX	20
DEV.ST	20
AVERAGE >55	45
MIN	40
MAX	50
DEV.ST	5
Age correlation	-0,17
T-VALUE	-0,66

The collected data on overconfidence across different age groups reveals a pattern that might initially seem to align with certain expectations about age and confidence levels (table 10). For the youngest cohort, those under 25, there is a moderate average level of overconfidence, with minimal variability, as indicated by the narrow range of scores and a standard deviation of 5. The 26-35 age group exhibits greater variability, with a standard deviation of 25.48, suggesting diverse levels of overconfidence that could reflect a transition period in their professional and personal lives

The 36-45 age bracket shows the highest average overconfidence score of 60, yet with a smaller range of scores and a lower standard deviation than the 26-35 group, pointing to a more uniform level of overconfidence. Notably, the data for the 46-55 age group, with an average, minimum, and maximum score of 20, and a standard deviation of 0, because there was only a single respondent, casting doubt on the validity of conclusions for this age range. Individuals over 55 have an average score that is equal to the under-25 group, with a similarly small range and standard deviation, which could indicate a pattern or may simply reflect an insufficient number of observations.

The Pearson correlation coefficient calculated between age categories (assigned values from 1 to 5) and overconfidence scores is -0.17. This negative correlation suggests that younger individuals tend to exhibit higher overconfidence. However, the correlation is not statistically significant, with a t-value of -0.66, indicating that the relationship observed in the sample does not provide strong evidence to support a definitive conclusion about age and overconfidence.

While the pattern observed might seem to confirm the literature that suggests younger individuals are more overconfident, the lack of statistical significance means that this finding is not reliable enough to assert as a general truth. The analysis is likely compromised by the limited and uneven data points across the age groups. To draw more robust conclusions, a larger and more evenly distributed sample across all age categories would be necessary. Therefore, while the results are intriguing and may hint at a trend consistent with existing beliefs, they cannot be deemed conclusive without further investigation and more comprehensive data.

4.4.2.4 Managers Miscalibration: Experience in the Field

(table 11)

MISCALIBRATION: EXPERIENCE IN THE FIELD	
AVERAGE <1 YEAR	40
MIN	40
MAX	40
DEV.ST	0
AVERAGE 1-3 YEARS	27,5
MIN	0
MAX	60
DEV.ST	21,65063509
AVERAGE 4-6 YEARS	65,71428571
MIN	40
MAX	70

DEV.ST	10,49781318
AVERAGE 7-10 YEARS	80
MIN	80
MAX	80
DEV.ST	0
AVERAGE >10 YEARS	44
MIN	20
MAX	70
DEV.ST	16,24807681
CORRELATION MISCALIBRATION/EXPERIENCE AS MANAGERS	0,16
T-VALUE	0,63

Analyzing the relationship between field experience and overconfidence levels presents a pattern that is somewhat reflective of common expectations (table 11). Individuals with less than one year of experience exhibit a score of 40, and only a single respondent in this category is denoted by the 0 standard deviation.

As we move to the group with 1 to 3 years of experience, there is a noticeable dip in the average overconfidence score to 27.5. This group demonstrates the greatest variability in confidence, with a standard deviation of 21.65 and scores ranging from 0 to 60. This could illustrate the variable confidence levels as individuals confront the realities and challenges of their chosen field in their early careers.

The 4 to 6 years experience bracket shows a substantial rise in the average overconfidence score to approximately 65.71, with a narrower range of scores (from 40 to 70) and a standard deviation of around 10.50, hinting at growing confidence as individuals become more established and proficient in their roles.

A stark peak in overconfidence is observed in those with 7 to 10 years of experience, all reporting a maximum score of 80. With a standard deviation of zero, this category assertively indicates the presence of a single observation, which, while it aligns with the hypothesis that confidence increases with experience, also underscores a significant limitation in the data due to the lack of multiple respondents.

For professionals with over 10 years of experience, the average overconfidence level decreases to 44, with a range that spans from 20 to 70 and a standard deviation of 16.25. This spread suggests a more complex relationship between experience and overconfidence, possibly indicating a plateau or even a decline in the overestimation of one's abilities.

The Pearson correlation coefficient, at 0.16, suggests a slight positive association between years of experience and overconfidence levels. However, with a t-value of 0.63, this correlation does not reach statistical significance, indicating that the sample data does not provide strong evidence of a meaningful relationship.

Despite the findings that seem to mirror the theoretical expectation that more experience is associated with higher overconfidence, the statistical analysis does not provide significant evidence to substantiate this trend. The limited sample size, particularly the instances where entire categories are based on a single observation, constitutes a notable limitation. This constraint on the data set undermines the ability to draw statistically robust conclusions and highlights the necessity for a broader and more varied set of responses to truly verify the apparent relationship suggested by the literature.

4.4.2.5 Managers Miscalibration: Educational Level

(table 12)

MISCALIBRATION: EDUCATIONAL LEVEL	
AVERAGE DIPLOMA	58,33333333
MIN	20
MAX	80
DEV.ST.P	21,14762923
AVERAGE BACHELOR DEGREE	60
MIN	35
MAX	85
DEV.ST.P	23,31844763
AVERAGE MASTER DEGREE	42,5
MIN	0
MAX	70
DEV.ST.P	17,39926363
AVERAGE DOCTORATE	40
MIN	40
MAX	40
DEV.ST.P	0
CORRELATION MISCALIBRATION/EDUCATIONAL LEVEL	0,338926817
T-VALUE	1,440995864

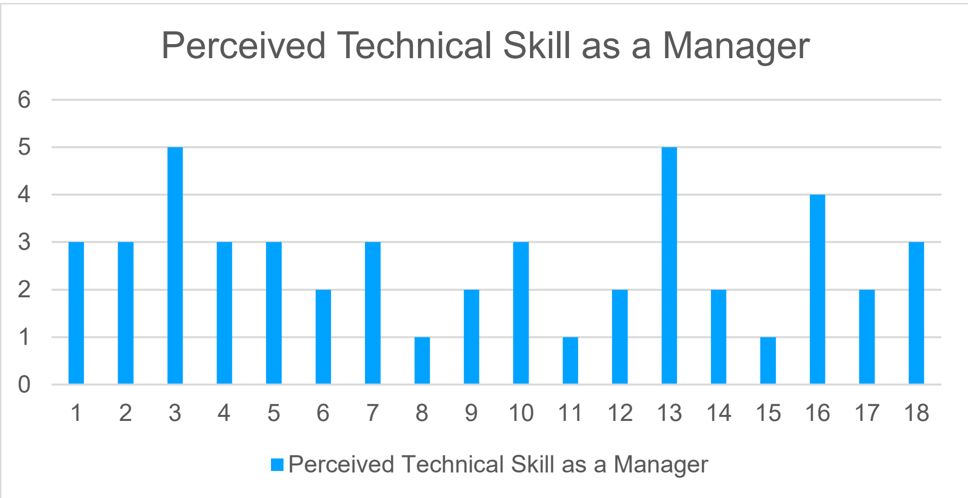
Table 12 presents a comparison of overconfidence levels among individuals with varying degrees of educational attainment. Notably, it is the bachelor's degree holders who exhibit the highest average overconfidence score, distinguishing themselves within the spectrum of educational qualifications considered.

When delving into the relationship between education and overconfidence, the Pearson correlation coefficient indicates a slight negative trend. This would suggest that individuals with lower academic qualifications may have a tendency towards higher levels of overconfidence. Nevertheless, this observed correlation lacks statistical significance, as evidenced by the t-value. The implication here is that, while there might be a suggested trend, the data does not provide strong evidence to assert that this is a pattern that holds true across the wider population.

The limitations inherent in the dataset are significant. They stem chiefly from the small number of observations for certain levels of education, particularly those where only one or two responses were recorded. This limitation is critical as it raises concerns about the representativeness of the findings. In some educational categories, the presence of a single respondent can dramatically skew the average score, and thus the perceived level of overconfidence for that group. For the analysis to be considered robust, a larger and more diverse set of observations is essential. This would provide a more reliable foundation for evaluating the relationship between educational attainment and overconfidence, ensuring that any conclusions drawn are reflective of a broader and more varied sample of the population.

4.4.2.6 Managers Miscalibration: Perceived Technical Skill as Managers

(figure 10)



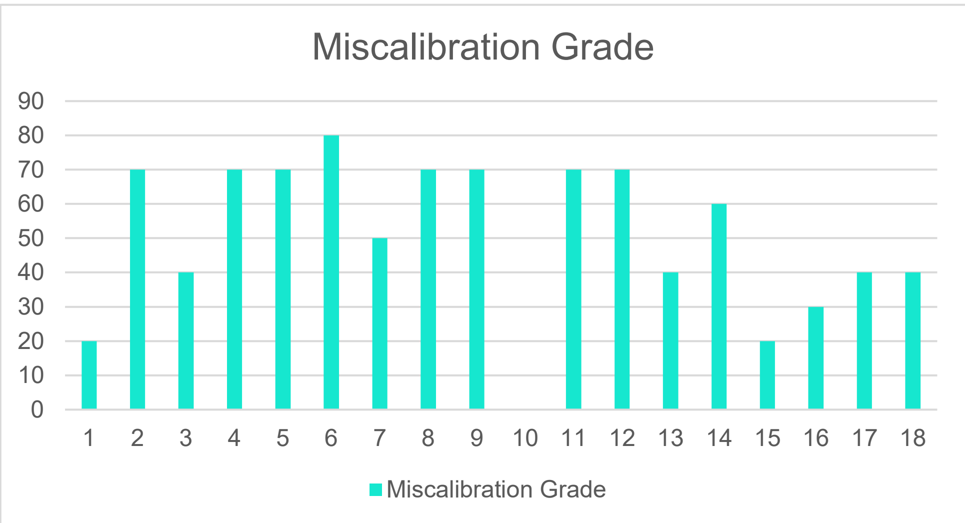


Figure 10 illustrates a comparison between respondents' perceived technical skills (rated on a scale from 1 to 5, where 1 indicates 'very low' and 5 'very high') and their degree of miscalibration. A Pearson correlation analysis reveals a relationship of -0.317443462, with a t-value of -1.954861024. The associated p-value is 0.06830123, which is not less than the standard significance level of 0.05 but is under 0.1, suggesting a weak statistical significance.

One reason for this trend, where individuals with a lower perception of technical skills exhibit greater miscalibration, may be compensatory overconfidence: to counter feelings of insecurity or perceived inadequacy, they may display greater certainty as a way to compensate for or mask their uncertainties.

Another reason for the observed relationship might be that managers are miscalibrated in their perceived technical skills. This underconfidence could lead them to underestimate their abilities, resulting in a lower self-reported technical skill level that correlates with higher miscalibration scores.

Implications of this finding are multifaceted. If managers are underconfident in their technical skills, this could impact their decision-making processes, potentially leading to overly cautious or conservative approaches. It could also affect their leadership effectiveness, as underconfidence might translate to less assertive team management and a reluctance to champion innovative solutions.

4.4.2.7 Managers Miscalibration: Cost Evaluation and Profit Margins

The examination of the relationship between overconfidence, quantified as miscalibration, and the variance between predicted and actual costs for a specific project, reveals statistically significant findings. The method employed for this analysis involved calculating the average cost deviations across various datasets and correlating these with the respondents based on their group membership. It is important to note that only 15 out of 18 managers are part of the groups included in the datasets.

The Pearson correlation coefficient between the degree of overconfidence and cost discrepancy is 0.501502144, with a p-value of 0.04998929, which just breaches the threshold for statistical significance, indicating a moderately positive relationship. This implies that higher levels of overconfidence among managers are associated with greater discrepancies in cost predictions.

Conversely, the relationship between the degree of overconfidence and the discrepancy between expected and actual profit margins is represented by a Pearson correlation coefficient of -0.495295058, with a p-value of 0.05651238. Although this p-value slightly exceeds the traditional cutoff for statistical significance, it suggests a negative correlation: as overconfidence increases, profit margins tend to decrease.

To delve deeper into the relationship between overconfidence and financial discrepancies in project management, two separate regression analyses were conducted. In the first regression, the discrepancy between projected and actual costs served as the dependent variable (Y), while the degree of overconfidence was the independent variable (X). This regression would help to understand whether a higher level of overconfidence among managers is predictive of larger discrepancies in cost estimations.

In the second regression, the dependent variable was the discrepancy between expected and actual profit margins, and again, the degree of overconfidence was the independent variable. This analysis aims to determine if overconfidence influences the accuracy of profit margin predictions, potentially leading to expectations that do not align with the final financial outcomes.

(table 13)

```
Residuals:
Min       1Q  Median      3Q     Max
-20.949 -12.085  -3.221  16.357  26.638
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
MISCALIBRATION  0.4112     0.1968    2.09  0.05683.
Residual standard error: 16.97 on 13 degrees of freedom
Multiple R-squared:  0.2515,    Adjusted R-squared:  0.1939
F-statistic: 4.368 on 1 and 13 DF,  p-value: 0.05683
```

Cost Discrepancy = 0.4112 × Miscalibration + ε

The first regression analysis findings provide insight into the impact of miscalibration on cost discrepancies. The residuals, which measure the differences between the observed values and the values predicted by the model, range from -20.949 to 26.638. This spread suggests that there is some variance in the model's predictions compared to the actual values.

The coefficient for miscalibration is 0.4112, indicating that there is a positive relationship between the degree of miscalibration and the discrepancy in cost estimations. However, the standard error of this estimate is 0.1968, and the t-value is 2.09, which corresponds to a p-value of 0.05683. This p-value is slightly above the conventional threshold of 0.05 for statistical significance, denoted by the dot next to the p-value, suggesting marginal significance. In practical terms, while the model indicates that higher miscalibration is associated with greater cost discrepancy, the relationship is not statistically reliable by strict standards.

The residual standard error of 16.97 on 13 degrees of freedom gives a sense of the average distance that the data points fall from the regression line. The Multiple R-squared value of 0.2515 shows that approximately 25.15% of the variability in cost discrepancy can be explained by the model, which is not very high, but not negligible either.

Regarding the p-value of the F-statistic in the regression analysis, it stands at 0.05683, which does not fall below the commonly accepted significance threshold of 0.05. This implies that the overall model, while suggestive of a relationship between miscalibration and cost discrepancies, does not meet the conventional criteria for statistical significance.

Nevertheless, considering the p-value is very close to the threshold, it indicates that the model could still be of interest. The proximity to significance suggests that there may indeed be a trend worth noting, and it could be meaningful in practical applications, especially if supported by additional data or corroborated by further studies.

(table 14)

```
Residuals:

    Min       1Q   Median       3Q      Max

-35.856 -11.155  -1.795  17.329  34.359

Coefficients:

                Estimate Std. Error t value Pr(>|t|)

MISCALIBRATION   -0.4866     0.2367  -2.056   0.0605.

Residual standard error: 20.42 on 13 degrees of freedom

Multiple R-squared:  0.2453,    Adjusted R-squared:  0.1873

F-statistic: 4.226 on 1 and 13 DF,  p-value: 0.06047
```

Profit Margins Discrepancies = -0.4866 × Miscalibration + ε

Table 14 examines the relationship between miscalibration and the percentage difference between expected and actual profit margins. The residuals suggest that the model's predictions deviate from the actual values by as much as -35.856 to 34.359, with a median close to zero, indicating that the model may have a slight tendency to overestimate or underestimate across the sample.

The coefficient for miscalibration is -0.4866, which suggests that an increase in miscalibration is associated with a decrease in the percentage margin discrepancy. In practical terms, it seems that as overconfidence increases, the actual profit margins are less than expected. The negative sign of the estimate supports this inverse relationship. However, with a standard error of 0.2367 and a t-value of -2.056, the p-value for this coefficient is 0.0605, which is slightly above the 0.05 threshold for statistical significance. This indicates a trend that approaches significance but is not conventionally significant.

The residual standard error of 20.42 on 13 degrees of freedom indicates the model's prediction error, which is relatively high. The Multiple R-squared value of 0.2453 shows that about 24.53% of the variability in the percentage difference between expected and actual margins is explained by the model, which is a moderate amount.

The F-statistic and its associated p-value (0.06047) test the overall significance of the regression model. Like the individual coefficient's p-value, the F-test's p-value is above the conventional threshold for significance, indicating that the model is not strictly significant.

The implications of both regression analyses and the Pearson correlation provide a nuanced understanding of how overconfidence, expressed as miscalibration, impacts financial forecasting in project management. The first regression indicates a positive association between overconfidence and the discrepancy between expected and actual costs, suggesting that as managers become more overconfident, the likelihood of underestimating costs increases. This could lead to budget overruns and can affect the overall financial health of a project.

The second regression shows an inverse relationship between overconfidence and profit margins, with the data suggesting that higher levels of overconfidence correspond with reduced profit margins. This could imply that overconfident managers might set overly optimistic revenue expectations or fail to anticipate potential issues, leading to profit margins that are lower than expected.

The implications of these findings are significant for organizational practice and suggest a need for interventions aimed at calibrating manager confidence levels. Training programs that improve estimation skills and foster a culture of realistic expectation-setting could be beneficial. Additionally, implementing structured review processes that challenge and scrutinize cost and revenue forecasts could help mitigate the financial risks associated with overconfidence.

Moreover, these results underline the importance of psychological factors in financial decision-making. Organizations may consider integrating behavioral finance insights into their strategic planning and decision-making frameworks to account for cognitive biases such as overconfidence.

In the upcoming section, the analysis will extend to the exploration of relationships involving the 'better than average' bias.

4.4.3 Overconfidence: Better-than-average Effect Results

In the following sections, we will delve into the presence of the better-than-average effect, a cognitive bias indicative of overconfidence. This phenomenon was investigated through a hypothetical scenario presented to the study participants. In this scenario, participants were part of a group of 100 project peers, all with comparable skills and experience. They were informed that at the project's conclusion, the individual with the best performance would receive a reward.

To gauge their perceived standing, participants were asked to predict their performance by ranking themselves on a percentile scale from 1 to 100, with 1 being the lowest performance and 100 the highest. This self-assessment was designed to measure the better-than-average effect. For example, positioning oneself at the 70th percentile would suggest a belief that their performance was better than 70% of their peers, reflecting a degree of overconfidence of 20 points above the median expectation. Such a self-placement divergent from the 50th percentile—where one would expect to be if all are equal—captures the essence of the better-than-average effect.

The analysis continued with the application of the Pearson correlation to assess if managers exhibited a better-than-average effect more significantly than the control group. To enhance the robustness of our analysis, we also conducted a Wilcoxon test. This non-parametric test was employed to evaluate if there was a statistically significant difference in the better-than-average effect between managers and the control group. The Wilcoxon test is particularly useful in situations where the data do not meet the assumptions required for parametric tests, providing a reliable measure of comparison without the need for a normal distribution. Furthermore, to explore the distribution of the better-than-average effect specifically within the manager group, we examined whether our observations were consistent with the patterns reported in existing literature.

4.4.3.1 Managers vs Control Group

To analyze the difference in the better-than-average (BTA) effect between managers and the control group, and to determine if one group exhibits it more than the other, respondents were categorized with the number '1' for managers and '0' for the control group. This categorization facilitated the examination of correlations between group membership and the degree of BTA bias exhibited. Following the correlation analysis, a Wilcoxon test was performed.

(table 16)

BTA: MANAGERS VS CONTROL GROUP			
AVERAGE MANAGERS	19,38888889	**AVERAGE CONTROL GROUP**	4,36
MIN	-20	**MEDIAN CONTROL GROUP**	20
MAX	50	**CORR MANAGER/CONTROL**	0,28889
DEV.ST	20,49156707	T VALUE	1,734206
MEDIAN MANAGERS	26,5	P-VALUE	0.09222
	WILCOXON P-VALUE		0.09472

Table 16 shows a comparison of the better-than-average (BTA) effect between managers and a control group. The average BTA score for managers is approximately 19.39, with a range from -20 to 50, and a median of 26.5, which suggests that on average, managers rated themselves as having better-than-average abilities. The control group, however, has a much lower average BTA score of 4.36 and a median score of 20.

The Pearson correlation coefficient between managers and the control group is 0.28889, with a corresponding t-value of 1.734206 and a p-value of 0.09222. This p-value is not below the commonly accepted threshold of 0.05 for statistical significance but is less than 0.1, indicating a weak statistical significance at the 10% level. It suggests there may be a mild positive relationship between being a manager and exhibiting a higher degree of the BTA effect.

The Wilcoxon test results in a p-value of 0.09472, which, similar to the Pearson correlation, does not meet the 0.05 significance threshold but is significant at the 10% level. This p-value from the Wilcoxon test implies that there is a statistically significant difference at the 0.1 level between the BTA scores of managers and the control group, with managers showing a greater tendency towards the BTA effect.

The implication of the findings could be that managers tend to exhibit a higher degree of better-than-average bias, possibly due to the relational component inherent in their roles. The nature of managerial work often requires interactions that may compel managers to present themselves as more confident than they might truly feel, especially in relationships with clients and subordinates.

This perceived necessity to appear confident could be a professional facade adopted by managers to inspire confidence in their leadership abilities, to maintain morale among their teams, or to assure clients of their competencies and the viability of their projects. This phenomenon can lead to a systemic overestimation of abilities or performance, which is reflected in the higher BTA scores observed for managers compared to the control group.

Anyway, while these results indicate there is a statistically significant difference between the two groups at the 10% level, they are not 'strictly' significant by more stringent criteria (e.g., the 5% level). Additionally, the relatively small sample size suggests that we should interpret these findings with caution. The limited sample size might not fully represent the larger population, and these results would benefit from further investigation with a larger group to confirm the trends observed in this analysis.

4.3.3.2 Managers BTA Bias: Gender

(table 17)

BTA GENDER			
AVERAGE MALE	22,3	**AVERAGE FEMALE**	15,75
MIN	-15	MIN	-20
MAX	50	MAX	49
DEV.ST	19,35484	DEV.ST	21,27645
MEDIAN MALE	30	**MEDIAN FEMALE**	15
CORR MALE/FEMALE	-0,15883		
T VALUE	-0,6435		
WILCOXON P VALUE	0.5021		

Table 17 compares the better-than-average (BTA) bias between genders. The average BTA score for males is 22.3, with a minimum of -15 and a maximum of 50, while females have an average BTA score of 15.75, with a minimum of -20 and a maximum of 49. The median BTA score is higher for males at 30 compared to 15 for females. The standard deviation is somewhat similar for both genders, with males at approximately 19.35 and females at around 21.27, indicating a wide range of BTA scores within each gender.

The Pearson correlation analysis, which assigned the value '1' to males and '2' to females, resulted in a correlation coefficient of -0.15883. This negative value suggests that males tend to exhibit the BTA effect more than females. However, the t-value of -0.6435 and the Wilcoxon p-value of 0.5021 indicate that the correlation and the difference in BTA scores between genders are not statistically significant.

While the analysis seems to support the narrative that males display the BTA effect more prominently, the lack of statistical significance, as reflected by both the t-value and the Wilcoxon test, means that any implications drawn from these results would be speculative. The data does not allow for firm conclusions to be made regarding gender differences in the expression of the BTA bias. Therefore, despite the apparent trend, the results should be interpreted with caution, and further research with a larger sample size and more rigorous statistical testing would be required to establish any definitive gender-related patterns in overconfidence.

4.3.3.3 Managers BTA Bias: Age

(table 18)

BTA: AGE			
AVERAGE <25	19	**AVERAGE 26-35**	17,8
MIN	10	MIN	-20
MAX	28	MAX	50
DEV.ST	9	DEV.ST	25,39379

AVERAGE 36-45	34,33	**AVERAGE 46-55**	30
MIN	30	MIN	30
MAX	38	MAX	30
DEV.ST	3,299832	DEV.ST	0
AVERAGE >55	0	**CORRELATION BTA/AGE**	-0,12003
MIN	0	T-VALUE	-0,48363
MAX	0		
DEV.ST	0		

The table displays the better-than-average (BTA) bias scores across various age categories. The youngest group (<25) has an average BTA of 19, with a range from 10 to 28. The 26-35 age group shows a slightly lower average BTA of 17.8 and a broader range, from -20 to 50, indicating greater variability within this cohort.

The 36-45 age category has an average BTA of 34.33, which is notably higher, with scores ranging from 30 to 38. However, the category for individuals aged 46-55 shows a single BTA score of 30, because there was only one observation in this age group, and thus a lack of variability.

To assess the relationship between age and the better-than-average (BTA) effect, age categories were assigned ordinal values from 1 to 5. The Pearson correlation coefficient derived from this analysis is -0.12003, which indicates a very weak negative correlation between age and BTA scores. This suggests that as age increases, the degree of the BTA effect tends to decrease. However, the corresponding t-value of -0.48363 demonstrates that this observed correlation is not statistically significant. Given these findings, the implications regarding age and BTA should be considered with caution, particularly in light of the non-significance and the small sample size in certain age categories, such as the 46-55 group where only one observation was noted.

Given these results and the presence of age groups with single observations, it is recommended that the company conduct surveys with more respondents. This would enable a more robust statistical analysis and potentially more conclusive insights into how age may relate to the BTA effect.

4.3.3.4 Managers BTA Bias: Experience

(table 19)

BTA: EXPERIENCE AS MANAGERS			
AVERAGE <1 YEARS	10	**AVERAGE 7-10 YEARS**	20
MIN	10	MIN	20
MAX	10	MAX	20
DEV.ST	0	DEV.ST	0
AVERAGE 1-3 YEARS	15	**AVERAGE >10 YEARS**	20,6
MIN	-20	MIN	0
MAX	50	MAX	38
DEV.ST	26,92582	DEV.ST	17,01294

AVERAGE 4-6 YEARS	**22,28**	**CORRELATION BTA/EXPERIENCE**	0,11
MIN	-15	T-VALUE	0,432029
MAX	49		
DEV.ST	20,63087		

Table 19 compares the better-than-average (BTA) bias across different experience levels. For those with less than 1 year of experience, the BTA score is 10, with no variability since there was only one observation.

Individuals with 1-3 years of experience have a wider range of BTA scores, from -20 to 50, with an average of 15 and a larger standard deviation of approximately 26.93.

Those with 4-6 years of experience show an average BTA of 22.28, with scores ranging from -15 to 49, and a standard deviation of 20.63, which suggests variability but less so than the 1-3 years group.

The group with 7-10 years of experience has a uniform BTA score of 20, with no variability, while individuals with over 10 years of experience show a slightly higher average BTA score of 20.6 and a range from 0 to 38, and a standard deviation of 17.01, indicating some variability but again a small sample size or uniformity in responses.

The correlation coefficient between BTA and experience is 0.11, with a t-value of 0.432029, indicating a very weak positive relationship between experience and BTA, which is not statistically significant. This weak correlation and the presence of categories with low variability or single observations suggest that further data collection and analysis would be needed for a comprehensive understanding of how experience levels influence the BTA effect.

4.3.3.5 Managers BTA Bias: Educational Level

(table 20)

BTA EDUCATIONAL LEVEL			
AVERAGE DIPLOMA	19,33333	**AVERAGE BACHELOR DEGREE**	10
MIN	-20	MIN	-15
MAX	49	MAX	35
DEV.ST.P	23,32143	DEV.ST.P	20,41241
AVERAGE MASTER DEGREE	20,625	**AVERAGE DOCTORATE**	38
MIN	0	MIN	38
MAX	50	MAX	38
DEV.ST.P	17,39926	DEV.ST.P	0
CORRELATION BTA/EDUCATIONAL LEVEL		0,131927349	
T-VALUE		0,53236257	

Examining the BTA effect across different levels of educational attainment (table 20), we observe that individuals with a diploma reported an average BTA score of around 19.33. This score is situated between the lower average BTA score of 10 for those with a bachelor's degree and a higher average of approximately 20.63 for master's degree holders. Notably, the doctorate holders' group presents an average BTA of 38, which, alongside a standard deviation of 0, because this figure was reported by a single respondent.

The ranges of BTA scores demonstrate variability among those with diplomas and bachelor's degrees, with standard deviations suggesting diverse self-assessments of abilities. However, the uniform BTA score in the doctorate category suggests a limited dataset from which to draw conclusions for that group.

The Pearson correlation between educational level and BTA, quantified as 0.131927, suggests only a weak positive trend. This correlation is not statistically supported by the t-value of 0.532363, which falls short of indicating significance.

Given these observations, the average BTA scores across education levels imply that higher education may not necessarily correlate with lower overconfidence. Yet, the presence of single-observation categories necessitates a cautious approach to these conclusions. For a more definitive analysis, a larger and more diverse respondent pool is essential, particularly to ensure robustness in categories currently represented by a solitary individual.

4.3.3.6 Managers BTA Bias: Case Studies Dataset

In this section, we will analyze the better-than-average (BTA) effect among managers who have been involved in the projects included in the datasets provided by the company. Out of the 18 survey participants, 15 managers' responses are examined. The focus will be on exploring how the level of BTA correlates with discrepancies between expected and actual profit margins, as well as between anticipated and actual costs as reflected in the datasets.

Additionally, the analysis will extend to provide further insights into the relational abilities of the managers who participated in the projects discussed in the earlier sections of Chapter 4. This will involve looking at the intersection of managerial overconfidence with their ability to manage relationships effectively within the project environment. The objective is to understand not just the financial implications of BTA but also how it might impact interpersonal dynamics and project leadership.

(table 21)

CORRELATION BTA/COST DISCREPANCIES	-0,003054233
T VALUE	-0,011012244
CORRELATION BTA/PROFIT MARGIN DIFFERENCES	-0,213524617
T VALUE	-0,788048172
CORRELATION BTA/PERCEIVED RELATIONSHIP SKILL	0,664325214
T VALUE	3,204600935

The data presents three distinct correlations: between better than average (BTA) bias and cost discrepancies, BTA bias and profit margin differences, and BTA bias and perceived relationship skills among managers who participated in projects provided by the company.

The correlation between BTA and cost discrepancies is -0.003054233 with a t-value of -0.011012244, indicating a negligible negative relationship. Similarly, the correlation between BTA and profit margin differences is -0.213524617 with a t-value of -0.788048172, suggesting a weak negative relationship. Both of these correlations lack statistical significance, as reflected by the minimal t-values. This implies that there is no substantial link between the level of BTA bias and discrepancies in costs or profit margins. Given the lack of significant findings, no further analysis regarding these relationships was deemed necessary.

A significant correlation has been identified between BTA bias and managers' self-assessed relationship skills. Managers rated their relationship skills on a scale ranging from very low to very high. These ratings were then converted into categorical variables, with values assigned from 1 to 5, corresponding to increasing skill levels. The Pearson correlation coefficient calculated from these data is 0.664325214, which is paired with a t-value of 3.204600935.

This strong correlation suggests that managers who perceive their relationship skills as higher also tend to exhibit a greater degree of BTA bias. This strong positive correlation indicates a significant relationship, suggesting that managers who perceive themselves as having higher relational skills tend to exhibit a higher degree of BTA bias. This finding merits attention as it underscores the potential impact of self-perceived relational abilities on managerial overconfidence. To further explore this relationship, the subsequent regression analysis was conducted:

(table 22)

```
Residuals:
     Min       1Q   Median       3Q      Max 
-15.7372 -15.7372 -15.7372  15.7372  15.7372 

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
Perceived Relationship Skills           16.8731     5.2653   3.2046  0.00691 **
Residual standard error: 15.737 on 13 degrees of freedom
Multiple R-squared:  0.4413,    Adjusted R-squared:  0.3984 
F-statistic: 10.269 on 1 and 13 DF,  p-value: 0.006906
```

BTA Bias = 16.8731 × Perceived Relationship Skills + ε

The regression output indicates a significant statistical relationship between managers' self-assessed relationship skills and their BTA (better than average) bias. The analysis uses the managers' ratings of their relationship skills, which have been categorized on a scale from 1 to 5, with these categories treated as a continuous predictor in the regression model.

The coefficient for perceived relationship skills is 16.8731, suggesting that for every one-unit increase in the relationship skills rating, there is an associated increase of 16.8731 units in the BTA bias score. This positive coefficient is statistically significant, as indicated by the t-value of 3.2046 and a corresponding p-value of 0.00691, which is well below the conventional alpha level of 0.05.

The F-statistic of 10.269 further supports the model's significance, with a very low p-value of 0.006906, indicating that the relationship between perceived relationship skills and BTA bias is highly unlikely to be due to random chance.

In conclusion, this model provides strong evidence that managers' perceptions of their relational abilities are significantly related to their tendency to exhibit a better-than-average bias, with higher self-assessments correlating with greater BTA bias.

The analysis indicating that managers exhibit a more significant than average (BTA) effect than the control group, coupled with the finding that a high BTA value is influenced by an elevated perception of one's relational skills, prompts the question: Why might this be the case?

One plausible explanation lies in the inherent demands of the managerial role, particularly in client-facing situations. Managers are often expected to lead, persuade, and build relationships, tasks that inherently require a high degree of confidence in one's interpersonal abilities. This expectation can create professional pressure to display a level of self-assurance that may not always match their actual skills.

An earlier analysis in the chapter, which indicated that democratic processes in the case studies yielded poorer outcomes in terms of cost analysis, raises another question: How might an overestimation of one's relational abilities be detrimental in managing democratic processes?

An overestimation of one's relational abilities can be particularly detrimental in democratic decision-making processes where a balanced and inclusive approach is vital. In such settings, managers with inflated confidence in their interpersonal skills might presume they can unduly influence the group's consensus. This presumption may lead them to dismiss or inadequately weigh differing viewpoints, reducing the decision-making process to a pursuit of majority agreement rather than a genuine synthesis of ideas. Consequently, this could result in decisions that are less robust and potentially overlook critical considerations, as the overconfident manager may fail to recognize and integrate the full spectrum of team insights into the final decision.

On the contrary, in contexts where unanimity is sought, the requirement for complete agreement compels all members to engage in deeper discussion and to entertain various perspectives until a common resolution is reached. This can diminish the adverse effects of overconfidence, as even the most self-assured members must listen to others in order to achieve consensus. In an environment where the consent of all is mandatory, managers who overestimate their relational skills might feel the need to temper their assertiveness to avoid alienating other team members, leading to more collaborative efforts.

Additionally, in decentralized and hierarchical decision-making processes, the influence of overestimating one's relational skills is less pronounced by the very nature of these systems. Decentralized processes distribute decision-making authority across various levels or individuals, diluting the impact of any single person's overconfidence. Hierarchical systems, on the other hand, have built-in layers of oversight where decisions are reviewed and potentially adjusted at multiple levels, providing a natural check on individual biases. Thus, the potential distortions caused by an inflated sense of one's relational capabilities are inherently mitigated in these types of decision-making structures.

In addition to conducting more extensive surveys and project evaluations using a larger data set, it is recommended that the organization implement regular self-assessment or self-check procedures. These self-assessments would motivate individuals, particularly managers, to regularly appraise their own judgments of their skills and decision-making abilities. By cultivating a climate of introspection and rigorous self-evaluation, the organization may assist its staff, especially those in managerial positions, in identifying and minimizing potential biases such as excessive self-assurance. Engaging in this activity can result in improved and efficient decision-making processes, hence boosting the overall performance and success of projects and organizational initiatives.

In the following sections, we will analyze the degree of anchoring among the respondents.

4.4.4 Anchoring: Results

Initiating the section on anchoring, we delve into how this cognitive bias was explored among the respondents. Anchoring occurs when individuals rely too heavily on an initial piece of information to make subsequent judgments. To investigate this, respondents were presented with a scenario where they were asked to imagine working for a company that sells auto parts. A Japanese company expressed an urgent need for a part sold by their company. It was mentioned that the auto parts company had sufficient material to meet this demand.

Respondents were informed about the production cost of the part (€10) and its normal selling price (€20). To some of the respondents, additional information was provided: during an initial negotiation, a misunderstanding occurred due to a translator's error, suggesting the Japanese company would accept a price of €32. This misunderstanding was immediately clarified, indicating the information was incorrect. The other part of the respondents did not receive this piece of information.

Subsequently, all respondents were asked to specify the maximum price that would make them happy, the average price they would consider fair, and the minimum price they would accept before refusing the deal. The aim was to determine whether respondents exposed to the misleading information would propose higher prices compared to those who were not provided with this information, thereby assessing the influence of anchoring on their price setting.

4.4.4.1 Anchoring: Managers Results

(table 23)

	IRRELEVANT ANCHOR SCENARIO			ONLY RELEVANT ANCHORS SCENARIO		
	TOP PRICE	MEDIUM PRICE	MINIMUM PRICE	TOP PRICE	MEDIUM PRICE	MINIMUM PRICE
AVERAGE MANAGERS	25,6	22,4	19,6	35,00	26,60	26,80
MEDIAN MANAGERS	25	22	20	27,50	18,50	20,00
WILCOXON TOP PRICE P-VALUE	0.5779					
WILCOXON MEDIUM PRICE P-VALUE	0.4154					
WILCOXON MINIMUM PRICE P-VALUE	0.9009					

Analyzing Table 23, it becomes evident that although there are differences between the average and median prices quoted by managers when exposed to non-relevant information (the incorrect price of €32) versus only relevant information, no definitive conclusions about anchoring can be drawn due to the Wilcoxon p-values.

The Wilcoxon test, which is a non-parametric method used to compare two paired groups, yields p-values that are not below the commonly accepted threshold for statistical significance (typically p <

0.05). With p-values of 0.5779 for the top price, 0.4154 for the medium price, and 0.9009 for the minimum price, the test does not indicate significant differences between the groups with and without exposure to the non-relevant price information. This could indicate that the managers either did not anchor to the incorrect higher price or that any anchoring effect was too small to detect with the sample size used in the study.

4.4.5 Planning Fallacy: Results

Now, we turn our attention to examining the phenomenon of planning fallacy. To facilitate this analysis, nine proxy questions were posed to respondents about their everyday lives. Responses were rated on a scale from -2 to +2, with higher scores indicating a greater degree of planning fallacy. The following results present an assessment of how this cognitive bias is reflected in the respondents:

(table 24)

AVERAGE MANAGERS	**1,277777778**
MIN	-4
MAX	5
DEV.ST.P	2,556159349
CORRELATION PLANNING FALLACY/GENDER	0,16523555
T-VALUE	0,670154049
CORRELATION PLANNING FALLACY/EXPERIENCE IN THE FIELD	-0,287596365
T-VALUE	-1,201131204
CORRELATION PLANNING FALLACY/AGE	-0,009719738
T-VALUE	-0,03888079
CORRELATION PLANNING FALLACY/EDUCATIONAL LEVEL	0,242728227
T-VALUE	1,000843815
CORRELATION PLANNING FALLACY/COST DISCREPANCIES	0,146816701
T-VALUE	0,545673889
CORRELATION PLANNING FALLACY/MARGIN PROFITS DIFFERENCES	0,095459058
T-VALUE	0,371407428
CORRELATION PLANNING FALLACY/RISK AVERSION	-0,011033764
T-VALUE	-0,042736187

The investigation into planning fallacy among managers reveals a nuanced landscape of this cognitive bias within the professional realm (table 24). On average, managers score a mild 1.28 on the scale designed to measure the propensity for planning fallacy, with individual scores ranging from -4 to 5. This range, alongside a standard deviation of approximately 2.56, suggests a considerable spread in the degree of planning fallacy among the managers, indicating varied levels of optimism or pessimism in their planning.

The correlations between planning fallacy and several demographic and professional factors provide an interesting insight. For instance, the weak positive correlation of 0.165 with gender and the slightly stronger negative correlation of -0.287 with experience in the field suggest subtle tendencies. However, the corresponding t-values, 0.670 for gender and -1.201 for experience, point to a lack of statistical significance in these relationships.

Similarly, when we consider age and educational level in relation to planning fallacy, the correlations are almost negligible for age and modest for educational level, with respective t-values far from indicating a significant relationship. This pattern continues as we look at the correlations of planning fallacy with cost discrepancies and margin profits differences explored previously in this chapter. The correlation coefficients are modest at best, with t-values of 0.546 and 0.371 respectively, again highlighting the absence of a strong connection.

Lastly, the correlation between planning fallacy and risk aversion is virtually non-existent, further emphasizing the broader finding from this analysis: there are no significant correlations between planning fallacy and the variables examined.

In conclusion, the data does not reveal any significant correlations that would suggest the planning fallacy among managers is closely linked to the demographic and professional variables studied. This indicates that while the planning fallacy is present among managers, its impact and manifestation do not show a consistent pattern across different attributes such as gender, age, experience, educational level, and attitudes towards risk, or even within the specific domain of project cost and profit margin predictions.

4.5 Implication of the findings

In this section, we synthesize the insights gleaned from our analyses and consider their implications for managerial behavior, decision-making processes, and organizational practices.

Firstly, we identified a negative correlation between overconfidence, as measured by miscalibration, and perceived technical skills among managers. This suggests a compensative overconfidence phenomenon, where managers may overrate their decision-making capabilities to compensate for perceived gaps in technical expertise. The implication here is multifaceted: while a certain level of confidence is necessary for leadership, it becomes vital to ensure that this confidence is well-grounded. Companies may need to implement comprehensive training programs that address both technical and decision-making skills to mitigate the risks associated with compensative overconfidence.

Secondly, our analysis revealed a positive relationship between miscalibration and discrepancies in both cost estimation and profit margins. This finding underscores a critical need for interventions within the company to improve project forecasting and budgeting processes. Solutions could include the adoption of more rigorous analytical tools, the introduction of checks and balances to challenge overconfident estimates, and the fostering of a culture of critical reflection on past project performance to better inform future estimates.

Thirdly, the research showed that managers exhibit a higher level of better-than-average (BTA) bias compared to a control group of non-managers. The implication of this is the necessity for continuous self-evaluation mechanisms within managerial roles. Such mechanisms could involve regular feedback sessions, 360-degree reviews, or the use of self-assessment tools to encourage managers to maintain a realistic view of their capabilities and performance.

Fourthly, within the group of managers involved in the projects analyzed in the dataset, we observed that BTA is positively related to their level of perceived relational skill. This correlation might be explained by the managerial role's inherent requirement to interact confidently with clients. However, this trait can have adverse effects in democratic decision-making settings. Since our analysis indicated that democratic processes were the least effective in decision-making, there's a clear indication that overconfidence in relational skills needs to be calibrated carefully. Managers should be aware of the potential drawbacks of overconfidence, particularly within collaborative decision-making environments.

Lastly, the comparison of project management methodologies revealed that agile and scrum approaches yielded better results than the waterfall method. This could be due to the iterative and incremental nature of agile and scrum, which may help mitigate the effects of miscalibration and BTA bias by allowing for regular reassessment and adaptation throughout a project's lifecycle. This finding suggests that adopting agile methodologies might serve as a counterbalance to the cognitive biases that can adversely impact project outcomes.

Taken together, these insights paint a complex picture of the interplay between managerial self-perception and effective decision-making. They point towards the need for a nuanced approach to manager training, one that balances the development of technical, relational, and evaluative competencies, and promotes decision-making frameworks that are both agile and reflective

The findings outlined thus far provide important preliminary insights into the cognitive biases affecting managerial decision-making. However, they also highlight the need for further research in this area. To enhance the robustness and applicability of these results, additional studies with larger sample sizes are crucial. Such studies would allow for a more comprehensive understanding of the nuances and broader trends associated with overconfidence, BTA bias, and their implications in various decision-making processes.

Moreover, the potential influence of anchoring and planning fallacy on project outcomes, as suggested by the analyses, calls for a deeper examination. To effectively analyze these biases, it would be beneficial to evaluate projects that are currently in progress. Real-time analysis of ongoing projects can provide a clearer picture of how these cognitive biases manifest and influence decisions throughout the lifecycle of a project.

Expanding the scope of the research to include a diverse array of industries and project types could also shed light on whether and how different contexts might amplify or mitigate the effects of these biases. Such insights would be valuable for developing targeted strategies to address the specific challenges faced by managers in different sectors.

In conclusion, while the current findings are instructive, they represent a foundation upon which more detailed and extensive research can be built. Future studies are needed to confirm these trends and to develop effective interventions that can be tailored to the nuanced demands of different managerial roles and project environments.

Chapter 5: Conclusions

This study embarked on the ambitious endeavor to uncover relationships between cognitive biases and financial outcomes within the rapidly growing and under-researched IT sector, a domain increasingly leveraged by numerous financial institutions. After delving into an extensive body of literature encompassing capital budgeting, project management, and behavioral finance, we analyzed data from a company active in this burgeoning field, detailing the performance of their IT projects. A meticulously crafted survey was deployed among the company's personnel to detect potential biases and draw correlations through statistical and regression analysis techniques. The investigation yielded several noteworthy empirical results:

Miscalibration and Financial Discrepancies:

A tangible link was established between miscalibration and the variances between expected and actual costs and profit margins. This connection was further substantiated through two separate regression analyses, cementing the influence of overconfidence on financial forecasting.

Miscalibration and Perceived Technical Skills:

The study corroborated the correlation between miscalibration and perceived technical skills, highlighting a compensatory dynamic where overconfidence in decision-making may mask a lack of technical acumen.

Better Than Average (BTA) Bias:

It was demonstrated that managers exhibit a higher BTA bias compared to a control group. This finding is indicative of the need for ongoing checks and balances in self-evaluation practices within managerial circles.

BTA and Perceived Relational Skills:

A significant relationship was discovered between BTA bias and managers' perceived relational skills. This suggests that managerial roles, which often necessitate heightened confidence in client interactions, may inadvertently bolster the BTA effect.

Democratic vs. Other Decision-Making Processes:

Democratic processes were found to be the least effective in terms of decision-making, as opposed to decentralized consensus-based or hierarchical processes.

Project Management Methodologies:

The analysis indicated that agile and scrum methodologies outperform the waterfall approach, which may be attributed to the continuous feedback loops inherent in agile frameworks that help mitigate cognitive biases.

Based on the outcomes of this investigation, a significant implication emerges: it is advisable for the concerned company, along with other entities involved in IT initiatives, to conduct further investigation into cognitive biases and their plausible repercussions during project assessments. Grasping and admitting these biases can furnish valuable perceptions into decision-making procedures, empowering organizations to devise tactics that alleviate their influences. This methodology not only amplifies the precision of project cost and margin evaluations but also augments the general prosperity and endurance of IT undertakings in the fluid and pivotal realm of information technology. This study's methodology comes with certain limitations that merit consideration. One of the primary constraints was the inability to monitor the projects in real time as they were being executed. This retrospective analysis limits our ability to capture the dynamic decision-making processes and the evolution of biases over the course of a project's lifecycle.

Additionally, not all case studies provided comprehensive information necessary to rule out rational explanations for cost and margin discrepancies. This gap in data may lead to an overestimation of the influence of cognitive biases where rational justifications exist but are not adequately documented or considered.

Another significant limitation pertains to the sample size of the survey respondents. With a relatively small group of subjects, there is a heightened possibility that some of the significant findings, even those at the 0.05 level, could be attributed to chance. The limited number of participants may not fully represent the broader population, which affects the generalizability of the results.

These limitations suggest that the conclusions drawn from this study, while indicative of certain trends, should be approached with caution. They underscore the need for future research with larger and more diverse samples, as well as studies that can observe decision-making processes as they unfold in real time to more accurately assess the impact of cognitive biases on project management.

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