Managing the costs of new product development projects:

a longitudinal case study at an automotive company

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The greatest achievement in life
is to become a guardian angel in another person's story.

For my parents.

Summary

The overarching research topic of this dissertation is the management of the costs of new product development projects. New product development (hereinafter NPD) is essential for most companies, as the introduction of innovative products is crucial for their long-term success. Due to the high level of uncertainty that comes with the innovative process of product development, the management of NPD costs is a highly challenging task. We illuminate the field of NPD cost management from two perspectives, which represent our research topics.

The first research topic of this thesis is the estimation of NPD costs. NPD costs are costs triggered by the activities that companies pursue to technically develop new products (i.e., labor costs of engineers, project managers, designers, and quality assessors, costs for tools and software required in NPD, costs of material and components required for testing and prototyping, and NPD-related overhead costs). Many authors have presented methods for product cost estimation in general, mostly focusing on overall product costs or direct material costs. Limited research is available about the estimation of the specific cost type of NPD costs. We conduct three studies to contribute to this gap. First, we give an overview of the status quo regarding NPD cost estimation. We do this by conducting a systematic literature review on methods for this purpose. Second, we develop and present the NPD cost benchmarking method. With this method, which is mostly built on external data, we add a new approach to the literature on NPD cost estimation methods. As third study in the context of NPD cost estimation, we present a case study in which we provide detailed, empirical insights on the challenges in NPD cost estimation, and on the application of the NPD cost benchmarking method in particular.

The second research topic of this thesis concerns decision-making processes during NPD projects. In this uncertain and dynamic environment, decision-makers often rely on heuristics to choose between alternative options for responding to unpredicted developments during NPD projects (for example, changes in market demands, technical challenges, or new information about competitors). Empirical insights are mostly missing about how such decisions are made. Our fourth study provides insights on the use of heuristics in ongoing NPD project managerial decision-making by conceptualizing and empirically testing the within-project NPD cost compensation heuristic.

This dissertation was supervised by Prof. Dr. Marc Wouters from KIT's chair of Management Accounting at the Institute of Management. It is written in English language and the author aims to obtain the title of Dr. rer. pol.

Table of contents

List of figures

List of tables

List of formulas

List of abbreviations

ABC	Activity-based cost estimation
BPNN	Back propagation neural network models
CFO	Chief financial officer
DPT	Development project type
EE	Department for electrical engineering
LoPd	List of products developed
LoPl	List of product launches
ME	Department for mechanical engineering
NPD	New product development
OEM	Original equipment manufacturer
PC	Product controlling department
SOP	Start of production

Preface

The thesis you are about to read was written during a research project conducted at the Karlsruhe Institute of Technology, and more precisely the Institute of Management's chair for Management Accounting. It is relevant to anyone interested in the field of cost management in new product development.

After finishing my master's degree in 2018, I was looking for my next big challenge and could not resist being offered the opportunity to start this exciting journey. I credit my motivation to pursue this path to my curiosity, my intention to expand beyond my comfort zone, and my urge to explore the boundaries of my capabilities. However, succeeding in this challenge would have never been possible if it were not for people who supported me on my way:

Thanks to my thesis supervisor! First and foremost, I want to thank the supervisor of this thesis, Prof. Dr. Marc Wouters. Marc, I am deeply grateful that you gave me the chance to work with you. Your commitment, your patience, and your enthusiasm were unparalleled. With your ability to light the spark of excitement for research, you have been a shining example for your profession.

Thanks to my project supervisors! For their trust, their support, and their leadership, I want to thank my project supervisors during the case study part of this thesis (in chronological order of joining the project): Dr. Frank Rösler, Felix Böbinger, Kai Siedlatzek, Dr. Stefan Niemand, and Michael Dinauer. You empowered me to pursue writing this thesis. I highly appreciate the level of trust you put in me during this research project as well as the always constructive and open communication.

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Thanks to my family! I would not be the person that I am today without some very special people in my life. To my parents Anita, Bruno, my sister Lena, and my girlfriend Denise: You are the four people I want to make the proudest of me. Thank you for your loving support! To Elisabeth, Karl, Rosmarie, Otto, Edith, Matthias, Margot, Karola, and Rita. Thank you for your role in shaping me into the person that I am today.

Thanks to my friends! Eleanor Roosevelt once said that "*many people will walk in and out of your life, but only true friends will leave footprints in your heart.*" I want to thank several companions that left particularly deep footprints during the last 30 years: Florian, Stefan L., Adrian, Andreas, Andreas, Bernd, Björn, Boris, Fabian, Hannes, Johannes B., Johannes M., Johannes T., Kai, Lukas, Marc, Martin, Max, Raphael, Stefan P., Timo, Tizian.

To all those people and especially to you, the reader, I hope you enjoy this thesis.

Karlsruhe, 2022
Michael Disch

1 Introduction

In this introductory chapter, we give a brief overview about the area of research that we contribute to with this work.[1] This will result in our research topics and the design we picked to conduct our studies. We also use this chapter to sketch out the structure of this thesis, providing guidance for the reader.

The overarching research topic of this dissertation is the management of the costs of new product development projects. New product development (hereinafter NPD) is essential for most companies, as the introduction of innovative products is crucial for their long-term success (Brown and Eisenhardt 1995; Cooper 2019; Cui and Wu 2017; Leonard-Barton 1992; Takeuchi and Nonaka 1986). NPD costs are expenses that occur during the process of technical product development and consist of labor costs triggered by people involved in the process (i.e. engineers, project managers, designers, and quality assessors), costs for tools and software required in NPD, costs for materials and components required for testing and prototyping, and NPD-related overhead costs. Due to the high level of uncertainty that comes with the innovative process of product development, the management of NPD costs is a highly challenging task (Davila 2000; Santiago and Bifano 2005; Song and Montoya-Weiss 2001; Tatikonda and Rosenthal 2000; Um and Kim 2018). As the costs for developing new products can be substantial for a company, solving this challenge is essential to avoid over- or underspending (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988). We illuminate the field of NPD cost management from two perspectives, which represent our research topics.

Our first research topic is the estimation of the costs of NPD projects. Many authors have presented methods for product cost estimation in general, mostly focusing on overall product costs or direct material costs. Several literature reviews discussing these methods exist (Altavilla and Montagna 2019; Niazi et al. 2006). However, limited research is available about the estimation of the specific cost type of NPD costs (e.g. Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003). We conduct three studies to contribute to this gap. First, we give an overview of the status quo regarding NPD cost estimation. We do this by conducting a systematic literature review on methods for this purpose. Second, we develop and present the *NPD cost benchmarking method*. With this method, which is mostly built on external data, we add a new approach to the literature on NPD cost estimation methods. As third study in the context of NPD cost estimation, we present a case study, in which we provide detailed, empirical insights on the challenges in NPD cost estimation, and on the application of the *NPD cost benchmarking method* in particular.

The second research topic of this thesis concerns decision-making processes during NPD projects. In this uncertain and dynamic environment, decision-makers often rely on heuristics to choose between alternative options for responding to unpredicted developments during NPD projects (for example, changes in market demands, technical challenges, or new information about competitors) (Sarangee et al. 2014; van Oorschot et al. 2010). Budget allocation in the context of NPD costs is usually considered as one-time decision (Ayal and Rothberg 1986; Blanning 1981; Chao and Kavadias 2008; Heidenberger and Stummer 1999; Loch and Kavadias 2002; Santiago and Soares 2020). Practice, however, shows, that resources are often allocated in sequential decisions, as a reaction to unexpected events during the development process. Empirical insights are mostly missing about how such decisions are made. Our fourth study provides insights on the use of heuristics in NPD project management decision-making. We conceptualize and empirically test the *within-project NPD cost compensation heuristic*, which prioritizes keeping NPD project costs in check through the idea of compensation.

[1] Large parts of this thesis are written in the first-person plural perspective for stylistic reasons. However, the author Michael Disch is independently responsible for the presented work.

This thesis comprises six chapters as shown in Figure 1. Besides this introductory chapter and a concluding chapter summarizing our work, this thesis' four main studies are presented in chapters two, three, four, and five. In the following, we will briefly introduce and summarize the four studies.

Figure 1: The six chapters that constitute this dissertation

The second chapter of this thesis is a systematic literature review focusing on the status quo regarding NPD cost estimation. We identify 39 publications that deal with methods for NPD cost estimation. We organize, classify, and analyze these publications to deliver a comprehensive overview of the challenging endeavor. Based on the cost estimation classification scheme of Niazi et al. (2006), we structure the cost estimation methods that are presented for the specific cost type of NPD costs. We further summarize guidelines for the successful setup, the application, and the maintenance of NPD cost estimation methods. We conclude with overviews about the two topics of uncertainty and data availability, which play a critical role in NPD cost management.

The third chapter introduces the *NPD cost benchmarking method*. As we could see that methods for NPD cost estimation are scarce, we contribute a novel approach to the literature. This technique builds on publicly available cost data from the annual reports of competitors. Extracting and adjusting that data allows setting up a regression model that results in NPD cost estimations for different product types. Additionally, a parametric part is added to account for company-specific cost structures and more flexibility in NPD cost estimation. The combination of regression model and parametric part is common for NPD cost estimation methods (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). However, building such a method on publicly available data to this extent is a novel approach.

In chapter four, we conduct a qualitative case study to examine the *NPD cost benchmarking method* in practice. The author of this thesis was actively involved in the implementation, application, and maintenance of the *NPD cost benchmarking method* at a case company. Building on observations, documents, emails, and discussion-style interviews, we deliver a comprehensive picture of challenges of NPD cost estimation and the *NPD cost benchmarking method* in particular. We describe these challenges through answering several research questions along the two dimensions credibility and data. As detailed empirical insights on the practical challenges in NPD cost estimation are scarce, we unveil several relevant aspects that contribute to our understanding regarding this topic.

In our fifth chapter, we conceptualize the *within-project NPD cost compensation heuristic*, to improve our understanding of organizational decision-making during NPD projects. Our concept guides decision-makers on the question of whether to compensate additionally required resources from available means or to allocate additional budgets to a development project, when faced with unexpected events. We add to the literature by introducing a novel concept, which prioritizes keeping NPD project costs in check. We further provide empirical support for factors that are associated with the application of the heuristic: We show that project cost compensation is larger, as there is a greater need to compensate NPD costs and more possibilities exist for finding compensation.

2 Estimating the costs of new product development projects: a literature review

Abstract

New product development (hereinafter NPD) is essential for most companies, as the introduction of innovative products is crucial for their long-term success. However, these activities are often uncertain, and the corresponding costs can be substantial. Estimating these NPD costs is a challenging process, as uncertainty is high and comparable data scarce. At the same time, a valid estimation and a corresponding target are essential to avoid over- or underspending. While manifold work is available about general product cost estimation methods, the estimation of NPD costs is still underrepresented in the literature. To set a common ground for methodological approaches to face the NPD cost estimation problem, we conducted a systematic literature review focusing on the character of such methods as well as aspects regarding their practical applicability. With this overview, we aim to inspire a growing body on this constantly rising challenge.

Keywords: *cost estimation; new product development; R&D; literature review*

2.1 Introduction

Most companies depend on repeatedly bringing innovative products to the market. Therefore, activities to develop those new products are substantial for the long-term success of many companies (Brown and Eisenhardt 1995; Cooper 2019; Cui and Wu 2017; Leonard-Barton 1992; Takeuchi and Nonaka 1986). The corresponding costs can be a significant financial burden for an organization (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988). Due to the uncertain and complex character of product development, managing these costs is a challenging task (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015).

Rising cost pressure and intense competition lead to a steadily growing importance of efficient NPD cost management (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). Estimating a project's NPD cost is one of the first and most important tasks. As the available resources for such projects are usually limited, a good estimation in the form of a target avoids over- or under-spending and therefore allows efficient distribution of resources among the entire company's development portfolio (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiao-chen et al. 2009).

The development of a new product is a complex and time-consuming process, and can easily take several years (Hamilton and Westney 2002; Relich 2016), which makes the estimation of the corresponding NPD costs a challenging process The main reason for this is a high level of uncertainty, which is common in NPD. Such uncertainty can be of technical (for example production processes, NPD lead time, or material costs) or commercial nature (for example customer demands, competitors' actions, or regulatory changes) (Davila 2000; Heller et al. 2012; Santiago and Bifano 2005; Song and Montoya-Weiss 2001; Tatikonda and Rosenthal 2000; Um and Kim 2018; Zhaodong et al. 2015).

Methods for product cost estimation are frequently discussed in the literature (Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Ruffo et al. 2006; Ruffo and Hague 2007). Several literature reviews were conducted giving systematic overviews about cost estimation methods concerning product cost estimation through the entire product life cycle (Altavilla et al. 2018; Niazi et al. 2006). None of these overviews specifically focusses on the unique character of NPD costs. The sub-stream of software development research is an exception, as various methods and reviews are available due to the large share of development cost compared to the overall product costs (Batra and Barua 2013; Bilgaiyan et al. 2017; Boehm et al. 1995; Rajper and Shaikh 2016).

A comprehensive overview of methods for NPD cost estimation in manufacturing environments is missing in the literature. Such an overview would help practitioners to find solutions for this challenge and researchers could use it as a foundation to develop further methods for the estimation of NPD cost. We conducted a systematic literature review to fill that gap. After identifying 39 publications through three systematic review steps, we analyzed the methods applied for NPD cost estimation following the classification scheme proposed by Niazi et al. (2006). In the next step, we conducted a content-based analysis, resulting in guidelines to a successful setup, application, and maintenance of such methods, as well as insights on the uncertainty problem and the challenge of data availability in NPD cost estimation.

Our findings emphasize the growing attention that the NPD cost estimation problem has received in the last two decades at the intersection of engineering and management. The practical relevance shows in the research approaches, as most of the work was done in the context of empirical studies, especially by pursuing case studies in various industries, such as the field of aviation and aerospace. However, most of these studies present their methods without detailed empirical insights regarding challenges that appear in actual NPD cost estimation in the organizational context: Scholars put a strong focus on their method itself, but largely neglect giving empirical evidence for the applicability of the respective method.

Our work delivers several relevant insights on NPD cost estimation methods. First, we could find most techniques from Niazi et al.’s (2006) scheme of cost estimation methods applied for this purpose, emphasizing the complexity and range of possible solutions to the problem. The outstanding methods for NPD cost estimation are *parametric methods*, *regression models*, *activity-based costing*, and *back-propagation neural networks*. Second, we find that most approaches combine aspects of multiple cost estimation techniques to achieve more efficient and accurate NPD cost estimations. As third insight, we deliver guidelines for the setup, the application, and the maintenance of NPD cost estimation methods in practice. These guidelines will help practitioners to implement such techniques. The fourth insight of this literature review is a confirmation that the aspect of uncertainty plays a significant role in NPD cost estimation. As this uncertainty is substantial to the process of NPD cost estimation, methods should pay special attention to this challenge. However, few present methods include specific techniques to face the aspect of uncertainty. As fifth insight, we identify the data availability problem as a major threat for NPD cost estimation. The comparability between cost data of previous projects to use for the estimation of future products is the key challenge in this regard.

The remainder of this chapter is structured as follows: First, we give an overview about the nature of NPD costs and highlight existing work on cost estimation in general and NPD cost estimation in particular. After an overview of our research design including a detailed structuring of the literature, we present our findings: We start by giving a general overview of the body of literature on NPD cost estimation methods before we describe each technique applied for NPD cost estimation and their interplay in more detail. We further present our guidelines for the successful setup, application, and maintenance of an NPD cost estimation method, before we talk about the challenges of uncertainty and data availability in this context. We conclude with a summary, limitations of this study, and an outlook on future research opportunities.

2.2 Literature on NPD cost estimation

To set a common base for the remainder of this work, we summarize relevant aspects from the existing literature towards the NPD cost estimation problem. First, we elaborate on general aspects regarding this cost type before we talk about the status quo regarding NPD cost estimation.

2.2.1 What are NPD costs?

Companies conduct product development activities to technically develop new products for their customers. In this context, product development covers all activities that a company undertakes for the ongoing technical development of new products to be put to market. Creating such technical innovation is crucial for a company's long-term success, as this allows to compete on innovative markets (Brown and Eisenhardt 1995; Cooper 2019; Cui and Wu 2017; Leonard-Barton 1992; Takeuchi and Nonaka 1986).

Product development activities are carried out closer to or further away from an actual product being sold to customers. Development activities further away from an actual product can be considered traditional research. An example would be to develop a new material for a spoiler to be put on cars in the future. Such activities are usually pursued without focus on a specific product. However, the material from our example could, under the right circumstances, rapidly be applied in an actual product, shifting its development to be very product-specific. Therefore, there is no clear distinction between traditional research and product-specific NPD activities. The latter, and the costs corresponding with it, is subject to this work. Such NPD activities usually follow a clearly defined product development process leading to the product's start of production and are subject to a different kind of product management than development activities without focus on a specific product (Bause et al. 2014; Echeveste et al. 2017; Morgan and Liker 2020).

Activities pursued in NPD rarely indicate the development of a new product from scratch. More often, new product development means adding, replacing and improving systems that were included in a previous product (Chwastyk and Kołosowski 2014; Gebhardt 2017; Kenton 2020). The reference system in the model of Product Generation Engineering (PGE) proposed by Albers et al. (2015), shows that NPD has to be understood with a generational mindset. The scholars show that NPD is rarely carried out as an actual greenfield development approach. In practice, companies usually develop new products by closely building on systems from a product's predecessor. Such predecessor systems can refer to the company's own products, but also to products put to the market by other organizations (Albers et al. 2017; Albers et al. 2019).

Scholars have given various definitions and descriptions of NPD. Sun and Wing (2005, p.295) describe NPD as a "complicated and time-consuming process in which several different activities are involved". Relich (2016, p.22) defines NPD similarly as "a complex and time-consuming process in which a product is designed, manufactured, tested and finally, launched on the market". Three major phases of NPD are presented by Hamilton and Westney (2002): concept, development, and execution. In the concept phase, first ideas and essential information are collected while setting a first business case for the product. The development phase takes this broad idea and converts it to a detailed development plan. That plan is the basis for the execution phase, in which the development is carried out leading to the new product. Other authors also define similar phases within NPD (Chen et al. 2010; Hamilton and Westney 2002; Rosenthal 1992; Wu et al. 2015). Although this phase-based approach recently shifted towards adaptions of concurrent engineering within NPD, it is still valid as a general framework (Sun and Wing 2005).

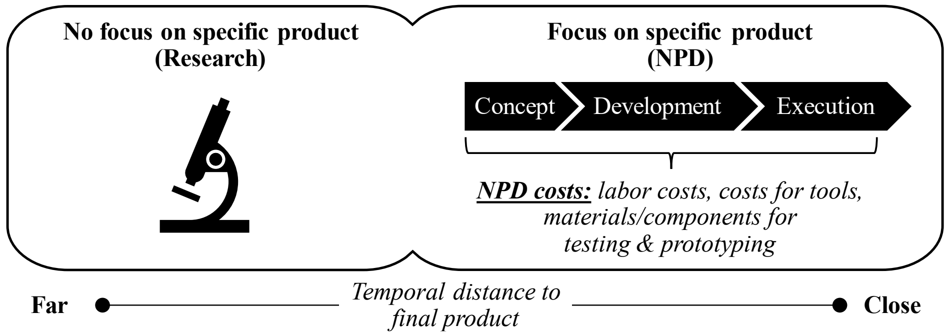

Figure 2: NPD costs discussed in this work in the context of product development activities

The costs that are affiliated with activities during the phases of NPD are called NPD costs. NPD costs occur from various activities and cost objects. One of the main components of NPD costs are labor costs. These can include direct as well as indirect labor costs or any other kinds of overhead depending on the accounting standard of the respective company. Labor costs in this regard are mostly triggered by the activities of employees such as engineers, project managers, designers, or quality assessors carrying out the development activities. Besides labor costs, expenses for tools or software required for the development process resemble typical NPD costs, just as costs of materials and components required for testing and prototyping (Tu and Xie 2003). Figure 2 gives an overview of NPD costs as they are discussed in this thesis.

2.2.2 What is known about NPD cost estimation?

Shorter product life cycles and rising competition on innovative markets have put immense pressure on companies to develop new products (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). Due to these conditions, NPD has become one of the, if not the most important activity for plenty of organizations (Duchi et al. 2014; Mousavi et al. 2015; Relich 2016).

The substantial financial means that are necessary to develop new products lead to the increasing relevance of actively managing NPD costs (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015). Due to the high level of uncertainty which is common in NPD, administering such significant financial resources is challenging (Davila 2000; Santiago and Bifano 2005; Song and Montoya-Weiss 2001; Tatikonda and Rosenthal 2000; Um and Kim 2018). A valid estimation for the resource requirements of a project in NPD is the first important task in this context. As the resources that are assigned to a project are not available to fund other activities of the firm, their correct estimation avoids over- or under-spending. With such a target, a company is enabled to manage its overall resources and the NPD projects in its portfolio in an efficient manner (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiao-chen et al. 2009). Without it, the company risks that development projects exceed their NPD cost targets. This can lead to substantial financial challenges due to the high resource requirements of such activities.

The consequences of a bad NPD cost estimation can be fatal. In the early phase of a product's life cycle, a company must make crucial decisions: Not all product ideas are brought to market, as many of them turn out to be unprofitable. To decide, whether a product will eventually contribute to the company's profits, a holistic profitability estimation is crucial. Here, the estimation of NPD costs plays a significant role that can push a project above or below the line of profitability (Gebhardt 2017; Johnson and Kirchain 2011; Tu and Xie 2003). The available resources for NPD are usually limited in terms of human and financial capital, which makes the estimation of NPD costs even more relevant. A bad estimate can lead to a lack or abundance of resources (Lambert and Sackett 1959; Relich 2016; Zhaodong et al. 2015). Both are undesired in terms of efficient resource management and therefore counterproductive for a company's long-term success. Having no estimation and therefore no cost target for the activities in this context at all was shown not to be beneficial in most cases, as this often leads to higher overall product costs (Everaert and Bruggeman 2002).

Uncertainty about the product as well as a lack of comparable data are the main reasons why NPD cost estimation is an extraordinarily challenging task. During the early phase of a product, many project parameters are usually not defined yet (Heller et al. 2012, 2012; Zhaodong et al. 2015). As product development is a fragile process, many premises about the product to be developed change during the early stages, while others are not defined yet. Besides this lack of information about the product in development, the distinct character of innovative products increases the complexity of the estimation process as experience and data from similar products are often missing. Although such comparisons to other projects are not the only way to estimate NPD costs, it usually resembles a helpful starting point (Hamilton and Westney 2002; Harrold and Nicol 1977, 1977; Yin et al. 2015).

The challenging aspects of product cost estimation are not new to the literature. Several studies have presented product cost estimation methods in theory and practice (Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Ruffo et al. 2006; Ruffo and Hague 2007). Besides publications discussing specific methods, extensive literature reviews about product cost estimation methods have been published (Altavilla et al. 2018; Niazi et al. 2006). Most methods presented in this context focus on material costs or overall product costs and largely neglect the unique character of NPD costs within a manufacturing company. In contrast to that stands the literature stream of software development where extensive work was published, mostly because of the development-centered cost structure in that industry (Batra and Barua 2013; Bilgaiyan et al. 2017; Boehm et al. 1995; Rajper and Shaikh 2016).

The literature is currently missing a comprehensive overview about the existing methods for NPD cost estimation within manufacturing environments. Such an overview would help managers in that area to increase the company's cost management abilities. For researchers, this would unveil the importance of such cost management tools and motivate to develop additional solutions for this managerial issue.

2.3 Research design

2.3.1 Identifying the body of literature

We conducted a systematic literature review summarizing the existing methods that are described for NPD cost estimation. We started with an initial, flexible literature review using Google Scholar as well as Web of Science, to get a better understanding of the topic. Afterwards, we formulated the search terms that we used for our subsequent, systematic literature review. Several steps were conducted for this systematic literature review, which we describe in the following as well as in Table 1.

The work we are searching for should fall into the description of *methods for NPD cost estimation in R&D*, leading to the five search terms: *method*, *NPD*, *cost*, *estimation*, and *R&D*. Besides these search terms we made sure to include relevant synonyms in our search query. We decided to connect the synonyms for each search term with the OR operator, while we connected the search terms with the AND operator. With this approach, we could make sure that all relevant aspects are mentioned. We further decided to look for the search terms in either the title, the abstract, or the keywords of publications as this ensured the relevance of each aspect in the work. The only exceptions were the search terms and synonyms for *cost* and *estimation*. As the cost estimation aspect is of high relevance for us, we wanted to focus on work that put these into the titles. As a further limitation to find relevant sources we decided to focus on literature from the subjects of *business, management, and accounting* as well as *engineering*. Applying this search strategy to the *Scopus* database in October 2019, delivered 1,757 results. Furthermore, we included 18 additional papers from our initial search. This led to our initial set of 1,775 publications.

In the next step, we excluded all results that did not deal with the desired topic based on their titles. As an example, we exclude the literature on software development, as we want to focus on manufacturing environments. We also excluded sources covering cost estimation for construction projects such as bridges, as that industry often develops products that are only produced a single time. This led to 495 papers. In the next step, we read the abstracts and excluded sources that did not fit our requirements, following the same criteria as in the previous step. This left us with 173 papers. These papers were then read in detail to exclude research that did not fit our topic. During this analysis, we mainly excluded publications that did not specifically deal with NPD costs, but either with other cost types or product costs in general. The 39 papers left represent our final set and were taken as a basis for this literature review. Figure 3 illustrates the exclusion steps we pursued to define our final set of publications. Based on these publications, we build our systematic literature review aiming for a general overview about the body of literature on NPD cost estimation methods, the different methodological approaches as well as practical aspects of NPD cost estimation.

Table 1: Literature review search strategy: methods for NPD cost estimation in R&D

Search query							
Search terms	Synonym 1	Synonym 2	Synonym 3	Synonym 4	Synonym 5	Synonym 6	Where?
Method	method*	technique*	approach	process	mechanism	system*	title, abstract, keywords
NPD	npd	product*	project*				title, abstract, keywords
Cost	cost*	expens*	spend*	budget*			title
Estimation	estimat*	target*	predict*	goal			title
R&D	r&d	research*	innovation	develop	design*	engineer*	title, abstract, keywords
Subject areas	Business, management, and accounting (1400) OR engineering (2200)[a]						
Search query (*Scopus*)	TITLE-ABS-KEY(method* OR technique* OR approach OR process OR mechanism OR system*) AND TITLE-ABS-KEY(product* OR npd OR project*) AND TITLE(cost* OR expens* OR spend* OR budget*) AND TITLE(estimat* OR target* OR predict* OR goal) AND TITLE-ABS-KEY(develop* OR research* OR innovation OR r&d OR design* OR engineer*) AND (LIMIT-TO (SUBJAREA,"ENGI") OR LIMIT-TO (SUBJAREA,"BUSI"))						
Initial set	1,775 publications (1,757 from systematic search using *Scopus* + 18 publications from unsystematic search using Google Scholar and Web of Science)						

Review process		
Review step	*Reasons for exclusion*	*Result of review step*
Title review	Area of software development (122 publications), construction projects (350 publications) or other reasons (808 publications)	After title review: 495 publications
Abstract review	Area of software development (6 publications), construction projects (74 publications), other cost types (61 publications) or other reasons (181 publications)	After abstract review: 173 publications
Detailed review	Not specifically NPD cost (113 publications), language neither English nor German (1 publication) or other reasons (20 publications)	After detailed review: **39 publications** (= final set)

[a] The numbers in brackets represent the codes for our subject areas within the *Scopus* database.

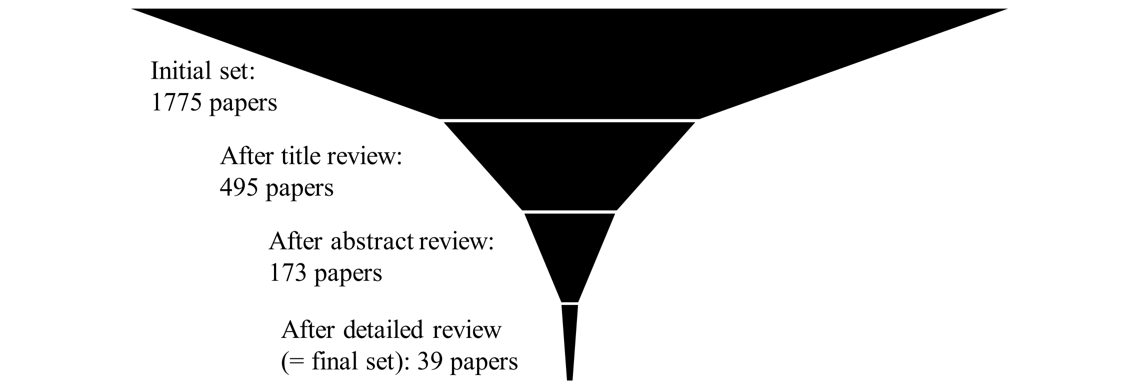

Figure 3: Illustration of the exclusion steps for the definition of the final set for our systematic literature review

2.3.2 Structuring the body of literature

We structure the literature on NPD cost estimation methods from two directions. First, we conduct an analysis in which we classify the publications based on several criteria. Table 2 summarizes the results of this descriptive analysis. These findings are the basis for chapters 2.4.1 and 2.4.2. The second direction for our analysis is more content-driven and is the basis for the identification of several practical and challenging aspects of NPD cost estimation. Table 3 summarizes the results of the content analysis based on relevant criteria. These findings are the basis for chapters 2.4.3, 2.4.4, and 2.4.5. In the following paragraphs, we describe the classifications we build our analyses on.

We classify the publications listed in Table 2 based on several categories: *literature types*[2], *research approaches, industries, and cost estimation methods*.

We want to investigate the literature streams that the NPD cost estimation methods are discussed in. To do so, we assign each publication to its primary topic as well as its publication type. We differentiate between publications in the streams of *engineering* (such as the *Journal of Engineering Design*, or De*sign Studies*), *management* (such as the *International Journal of the Econom*ics of Business, or *Foundations of Management*), *production* (such as *the International Journal of Production Economics, or* the *Journal of Cleaner Production*) as well as the *intersection of engineering and* management (such as *IEEE Transactions on Engineering Management*). In cases in which the publication medium did not explicitly list one of these target audiences, we categorized the source according to the best of our knowledge. Regarding the publication types, we distinct between *journals*, *book series*, *conferences, and proceedings*, and *contract research reports*. Furthermore, we included the rating per publication, according to the SCImago Journal Rank 2018 for an additional quality assessment.

We aim to understand how research regarding NPD cost estimation is conducted. For this purpose, we classify our publications into *conceptual* and *empirical work*. *Conceptual work (C)* in the context of this study refers to publications that are of theoretical nature. Authors of such publications present NPD cost estimation methods from a theoretical perspective, without connection to practical data of any kind. *Empirical work* in the context of this study refers to publications that draw their conclusions from practical insights from companies or other gathered data. We further cluster empirical work into the categories *case*

[2] For better readability, we did not include a publication's literatures stream, its literature type, and the corresponding rating explicitly in Table 2. See Appendix A for a detailed overview.

studies and *simulation/experiments*. *Case studies (Ec)* in the context of this work refer to NPD cost estimation methods that are presented as insights from organizational practice or methods that are proven to be functional based on empirical validation with organizational data. *Simulations and experiments (Es)* in the context of this work refer to studies that develop or validate their NPD cost estimation methods based on data from numerical simulations or experiments with human participants. As several authors combine aspects of more than one research approach, we assign more than one classification to some publications.

We classify the industries that the publications cover into the following categories: *aviation & aerospace (A), automotive (Au), electrical equipment and machinery (El), military equipment (Mi), miscellaneous manufacturing industries (MM),* and *power generation industry (Po)*. We base this classification either on the industry that is explicitly mentioned as the application industry of the NPD cost estimation method or the setting of the corresponding study. In cases in which no specific industry is explicitly mentioned, we classify the publication as *not specified (ns)*. As several authors combine insights from several industries, we assign more than one classification to some publications.

We build on previous work to cluster the different techniques that are applied for product cost estimation. Niazi et al. (2006) describe a classification scheme for cost estimation methods in their technique classification and methodology review. Altavilla et al. (2018) adopt the same structure in their taxonomy of cost estimation techniques. We build on this classification to structure the variety of different methods we identified within our sources. In most publications, the authors did not specifically state what technique they apply. Therefore, we made that classification in most cases based on our understanding after reviewing the publications in detail. Figure 4 illustrates all techniques according to the classification of Niazi et al. (2006). As we could find a publication that proposed a target costing approach for NPD cost estimation, we expanded the scheme for that technique. In chapter 2.4.2 we will elaborate on each technique in more detail.

We further classify each publication regarding the context of their methods. We differentiate between *single method (S)*, *combined methods (C)*, and *multiple methods (M)*. *Single method* in this context means that the publication describes an NPD cost estimation method that is based on a single cost estimation technique according to the scheme of Niazi et al. (2006). *Combined method* in this context refers to publications that describe an NPD cost estimation method that is based on the combination of several cost estimation techniques according to the scheme of Niazi et al. (2006). Publications that are categorized as *multiple methods* present more than one NPD cost estimation method in a comparing manner. In cases in which more than one technique according to the scheme of Niazi et al. (2006) is included, usually, a dominant technique can still be identified. We define the dominant technique as the core of the approach, which is being supported by other techniques. We mark such techniques in Table 2 with an underline.

We analyze the publications listed in Table 3 based on several categories: *setup, application, maintenance, uncertainty, and data.*

As we want to aid practitioners in the challenge of NPD cost estimation, we analyze the literature regarding aspects for the successful *setup, application, and maintenance* of an NPD cost estimation method. The three corresponding columns of Table 3 summarize relevant findings for each of the publications in our final set regarding these topics. In the column *setup*, we summarize key factors for a successful setup, core functionalities of the method as well as aspects of validation that are mentioned. While the proposed main phase of *application* in new product development is described if mentioned in the next column, the *maintenance* column describes whether the authors talk about any kind of maintenance activities in the context of their methods.

Closely related to the practical side of NPD cost estimation are the challenges of *uncertainty* and *data availability*. To understand how these topics are dealt with in the literature, we analyze the publications regarding these aspects. The corresponding columns in Table 3 summarize our findings in this context. The column *uncertainty* includes information about the way the method handles the common uncertainties in

NPD. The column *data* summarizes key findings regarding data in the context of NPD cost estimation, including its origin, the mentioning of potential threats through lacking data as well as potential solutions.

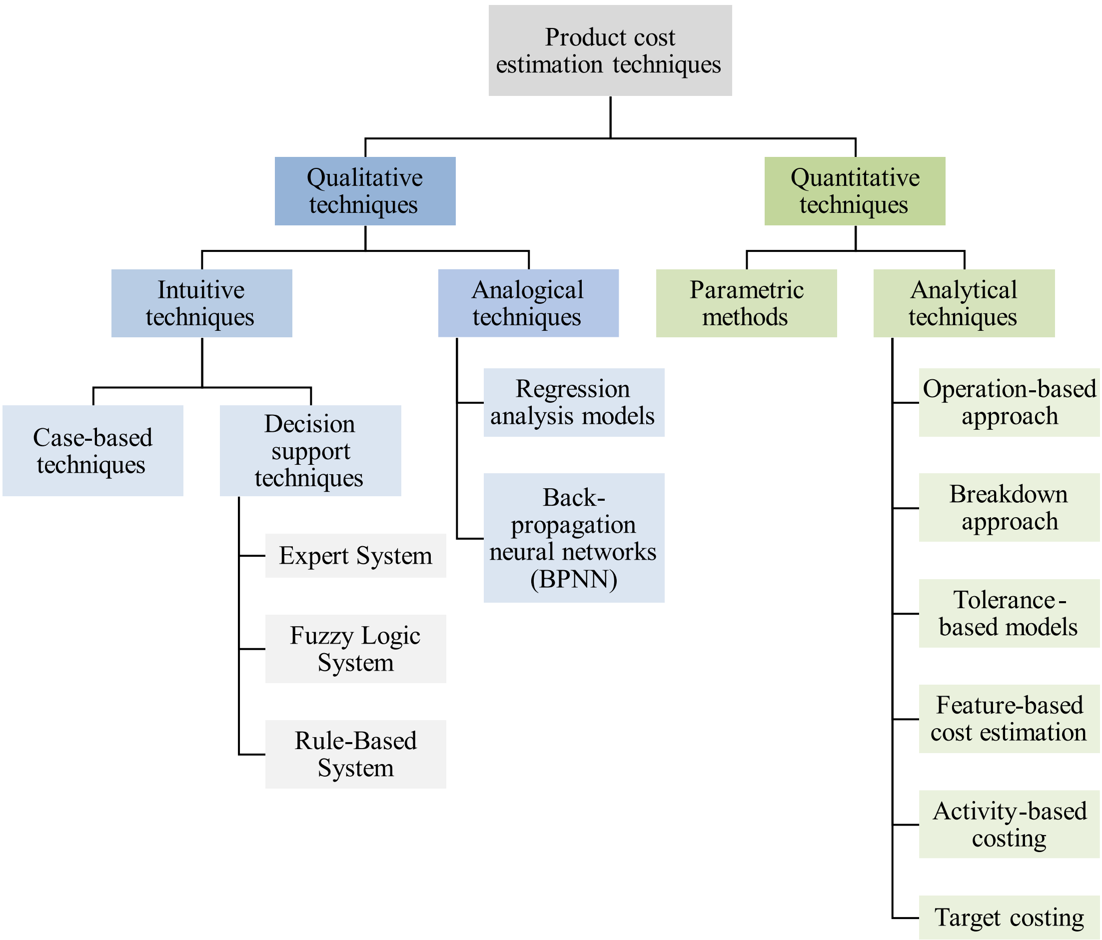

Figure 4: Overview of product cost estimation techniques according to Niazi et al. (2006)[3]

[3] The technique of target costing is not included in the scheme of Niazi et al. (2006). As we found such a technique applied for the purpose of NPD cost estimation, we expand the classification scheme.

Table 2: Overview of the findings of our systematic literature review – descriptive analysis

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Adelberger and Haft-Zboril (2015)	Systematischer Ansatz zur projekthaften Steuerung von Entwicklungskosten	CON (Controlling)	Ec	Au											x	x[a]								S
Bashir and Thomson (2001)	Models for estimating design effort and time	Design Studies	C, Ec	Po	x							x	x		x	x								C
Bashir and Thomson (2004)	Estimating design effort for GE hydro projects	Computers and Industrial Engineering	C, Ec	Po	x							x	x		x	x								C
Bashir et al. (2006)	Estimating design effort using a neural network methodology	International Journal of Industrial Engineering: Theory Applications and Practice	C, Ec	Po	x							x		x										S
Braun and Lindemann (2007)	A multilayer approach for early cost estimation of mechatronical products	Proceedings of ICED 2007, the 16th International Conference on Engineering Design	C	MM											x		x	x			x	x		C
Carreyette (1977)	Preliminary Ship Cost Estimation	Transactions of the Royal Institute of Naval Architects	C	MM											x	x	x	x			x	x		C

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	***Qualitative techniques***	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	***Quantitative techniques***	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Case (1972)	On the Consideration of Variability in Cost Estimating	IEEE Transactions on Engineering Management	C, Ec	MM	x	x		x	x						x̲		x̲		x̲					C
Chen et al. (2010)	Relative design cost estimation at design stage based on design features	Applied Mechanics and Materials	C, Ec	El											x̲		x̲	x	x		x̲	x		C
Chen et al. (2019)	Development cost prediction of general aviation aircraft projects with parametric modeling	Chinese Journal of Aeronautics	C, Es	A	x							x	x	x	x̲	x̲								C
Chen et al. (2020a)	Cost estimation for general aviation aircrafts using regression models and variable importance in projection analysis	Journal of Cleaner Production	C, Ec	A	x̲							x̲	x̲	x										C
Chen et al. (2020b)	Application of a PCA-ANN Based Cost Prediction Model for General Aviation Aircraft	IEEE Access	C, Ec	A	x̲							x̲		x̲										S
Chwastyk and Kołosowski (2014)	Estimating the cost of the new product in development process	Procedia Engineering	C, Es	MM	x	x	x								x̲	x̲								C

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Deng and Yeh (2010)	Applying least squares support vector machines to the airframe wing-box structural design cost estimation	Expert Systems with Applications	Ec	A	x							x		x	x	x								C
Gebhardt (2017)	Predicting indirect process costs of engineering change based on a task characteristic perspective	Proceedings of the International Conference on Engineering Design, ICED	Ec	Au											<u>x</u>	<u>x</u>								S
Harrold and Nicol (1977)	The prediction of design and development costs of civil airliners	Aeronautical Journal	C	A	x	x	x	x	x			x	x		x	x								M
Hinton and Moran (1983)	Cost Estimation of Research and Development Projects	American Society of Mechanical Engineers (Paper)	C	ns	x	x	x	x	x						x		x					x		C
Holtta-Otto and Magee (2006)	Estimating factors affecting project task size in product development - An empirical study	IEEE Transactions on Engineering Management	Ec	ns	x	x		x	x						x		x	x	x		x	x		C, M
Johnson and Kirchain (2011)	The importance of product development cycle time and cost in the development of product families	Journal of Engineering Design	C, Ec	Au	x							x	x		x	x	x					x		C

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Lambert and Sackett (1959)	Research and Development Cost Estimation	IRE (now IEEE) Transactions on Engineering Management	Ec	Mi, MM	x	x		x	x						x		x		x			x		M
Large et al. (1976)	Parametric Equations for Estimating Aircraft Airframe Costs	Rand Corp Rep R-1693-1-PA&E	Ec	A, Mi	<u>x</u>							<u>x</u>	<u>x</u>											S
Li et al. (2009)	R&D Costing Analysis and Prediction Modeling of Armored Vehicles	2009 8th International Conference on Reliability, Maintainability and Safety (ICRMS 2009)	C, Ec	Mi	x							x	x		<u>x</u>	<u>x</u>								C
Liu et al. (2013)	Method of product development cost estimating based on ProA hierarchical decomposition	19th International Conference on Industrial Engineering and Engineering Management	C, Es	MM											<u>x</u>		<u>x</u>					<u>x</u>		S
Love and Roper (2002)	Internal Versus External R&D: A Study of R&D Choice with Sample Selection	International Journal of the Economics of Business	C, Ec	MM	<u>x</u>							<u>x</u>	<u>x</u>											S
Mousavi et al. (2015)	An intelligent model for cost prediction in new product development projects	Journal of Intelligent & Fuzzy Systems	C, Ec	El	<u>x</u>							<u>x</u>		<u>x</u>										S

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Qian and Ben-Arieh (2008)	Parametric cost estimation based on activity-based costing: A case study for design and development of rotational parts	International Journal of Production Economics	Ec	MM											x	x	x					x		C
Relich (2016)	Computational Intelligence for Estimating Cost of New Product Development	Foundations of Management	C, Ec	ns	x	x		x		x		x		x										C
Riedrich and Sasse (2005)	Ganzheitliche Planung und Steuerung von Innovationsprojekten	CON (Controlling)	C	ns											x		x						x	S
Heller et al. (2012)	Bestimmung des Produktentwicklungsaufwands basierend auf Kennzahlen am Beispiel der Luftfahrzeugentwicklung	Entwerfen Entwickeln Erleben	C	A											x	x								S
Roy et al. (2001)	Quantitative and qualitative cost estimating for engineering design	Journal of Engineering Design	Ec	A	x							x	x		x		x				x	x		C
Salam et al. (2009)	Estimating design effort for the compressor design department: a case study at Pratt & Whitney Canada	Design Studies	C, Ec	A	x							x	x		x	x								C

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	**Title**	**Publication**	**Research approach**	**Industry**	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Scanlan et al. (2006)	DATUM project: Cost estimating environment for support of aero-space design decision making	Journal of Aircraft	Ec	A											x	x	x				x	x		C
Siddique and Repphun (2001)	Estimating Cost Savings when Implementing a Product Platform Approach	Concurrent Engineering: Research and Applications	C, Ec	El											x		x					x		S
Steck-Winter and Šebo (2008)	Effort Drivers in Engineering Design Cost Estimation	Konstruktion	C	ns											x	x	x					x		C
Sutopo et al. (2013)	An application of parametric cost estimation to predict cost of electric vehicle prototype	Proceedings of the 2013 Joint Int. Conference on Rural Information and Communication Techn. and Electric-Vehicle Technology, rICT and ICEV-T	Ec	Au											x	x	x				x	x		C
Tyagi et al. (2015)	Product life-cycle cost estima-tion: a focus on the multi-genera-tion manufacturing-based product	Research in Engineering Design - Theory, Appli-cations, and Concurrent Engineering	C, Ec	Po											x		x				x	x		C

Table 2: Overview of the findings of our systematic literature review – descriptive analysis (continued)

Author (Year)	Title	Publication	Research approach	Industry	**Qualitative techniques**	***Intuitive techniques***	Case-based techniques	Decision support techniques	Expert systems	Fuzzy logic systems	Rule-based systems	***Analogical techniques***	Regression analysis models	Back-propagation NNs	**Quantitative techniques**	***Parametric methods***	***Analytical techniques***	Operation-based approaches	Breakdown approaches	Tolerance-based models	Feature-based cost est.	Activity-based costing	Target costing	**Methods in context**
Wu et al. (2012)	Cost Estimating of Weapons Development Based on Rough Sets and ANN Learning	2012 International Conference on Intelligent Systems Design and Engineering Application	C, Ec	Mi	<u>x</u>							<u>x</u>		<u>x</u>										S
Wu et al. (2015)	Using weighted partial least squares to estimate the development cost of complex equipment at early design stage	Proceedings of IEEE International Conference on Grey Systems and Intelligent Services, GSIS	C, Ec	A, Au	<u>x</u>							<u>x</u>	<u>x</u>											S
Yin et al. (2015)	Development cost estimation of civil aircraft based on combination model of GM (1, N) and MLP neural network	Proceedings of IEEE International Conference on Grey Systems and Intelligent Services, GSIS	C, Ec	A	<u>x</u>							<u>x</u>		<u>x</u>										S
Zhaodong et al. (2015)	Development and Production Costs Estimating for Aviation Equipment Based on Uncertainty Design	Procedia Engineering	C	A	<u>x</u>							<u>x</u>	<u>x</u>											S

[a] The dominant techniques in each publication are marked with an underline

Table 3: Overview of the findings of our systematic literature review – content analysis

Author (Year)	**Setup**	**Application**	**Maintenance**	**Uncertainty**	**Data**
Adelberger and Haft-Zboril (2015)	Expert knowledge; cost-driving factors; key role of IT system; validation: comparison with cost data	Explicitly early phase	Regular total rework; regular adjustments	Experience of employees	Internal data; emphasizes that limited data threats NPD cost estimation
Bashir and Thomson (2001)	decomposition of dev. process; cost-driving factors; validation: comparison between methods	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; Jackknife technique
Bashir and Thomson (2004)	Expert knowledge; cost-driving factors; validation: comparison between methods	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Bashir et al. (2006)	Cost-driving factors; validation: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Braun and Lindemann (2007)	Expert knowledge; decomposition of dev. process; key role of IT system	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data
Carreyette (1977)	Expert knowledge; cost-driving factors	Explicitly early phase	Regular adjustments	Experience of employees	Internal data; non-internal data; emphasize threat of limited data to NPD cost estimation
Case (1972)	Expert knowledge; decomposition of dev. process	Explicitly early phase	No mentioning of maintenance activities	Expected cost as calculation from high/medium/low and standard deviation	Does not specify topic of data

Table 3: Overview of the findings of our systematic literature review – content analysis (continued)

Author (Year)	**Setup**	**Application**	**Maintenance**	**Uncertainty**	**Data**
Chen et al. (2010)	Cost-driving factors	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Relative cost difference due to features
Chen et al. (2019)	Cost-driving factors; validation: comparison with cost data; validation: comparison between methods	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; principal component analysis
Chen et al. (2020a)	Cost-driving factors; validation: comparison with cost data; validation: comparison between methods	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Chen et al. (2020b)	Cost-driving factors; key role of IT system; validation: comparison with cost data; validation: comparison between methods	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Non-internal data; emphasizes that limited data threats NPD cost estimation
Chwastyk and Kołosowski (2014)	Cost-driving factors; key role of IT system; validation: comparison with cost data	Explicitly early phase	No mentioning of maintenance activities	Change to different estimation method	Internal data
Deng and Yeh (2010)	Cost-driving factors; validation: comparison with cost data; validation: comparison between methods	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data
Gebhardt (2017)	Decomposition of dev. process; cost-driving factors; validation: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Assumption of time stability	Internal data

Table 3: Overview of the findings of our systematic literature review – content analysis (continued)

Author (Year)	**Setup**	**Application**	**Maintenance**	**Uncertainty**	**Data**
Harrold and Nicol (1977)	Expert knowledge; decom-position of dev. process; cost-driving factors	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Hinton and Moran (1983)	Expert knowledge; decom-position of dev. process	Explicitly early phase	Regular adjustments	Experience of employees	Internal data
Holtta-Otto and Magee (2006)	Expert knowledge; decom-position of dev. process; cost-driving factors; valida-tion: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Experience of employees	Internal data; emphasizes that limited data threats NPD cost estimation
Johnson and Kirchain (2011)	Expert knowledge; decom-position of dev. Process; cost-driving factors; valida-tion: comparison with cost data; validation: comparison between methods	Explicitly early phase	Regular total rework; regular adjustments	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Lambert and Sackett (1959)	Expert knowledge; decom-position of dev. process	No specific phase of application	Regular adjustments	Experience of employees	Internal data
Large et al. (1976)	Cost-driving factors	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Li et al. (2009)	Cost-driving factors; valida-tion: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Non-internal data; empha-sizes that limited data threats NPD cost estimation

Table 3: Overview of the findings of our systematic literature review – content analysis (continued)

Author (Year)	Setup	Application	Maintenance	Uncertainty	Data
Liu et al. (2013)	Expert knowledge; decomposition of dev. process	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data
Love and Roper (2002)	Cost-driving factors	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Does not specify topic of data
Mousavi et al. (2015)	Cost-driving factors; key role of IT system; validation: comparison with cost data; validation: comparison between methods	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Does not specify topic of data
Qian and Ben-Arieh (2008)	Decomposition of dev. process; cost-driving factors; validation: comparison with cost data; validation: comparison between methods	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Does not specify topic of data
Relich (2016)	Decomposition of dev. process; cost-driving factors; key role of IT system; validation: comparison with cost data; validation: comparison between methods	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Riedrich and Sasse (2005)	Cost-driving factors	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Target costing

Table 3: Overview of the findings of our systematic literature review – content analysis (continued)

Author (Year)	**Setup**	**Application**	**Maintenance**	**Uncertainty**	**Data**
Heller et al. (2012)	Expert knowledge; cost-driving factors; key role of IT system; validation: Comparison with cost data	Explicitly early phase	Regular adjustments	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Roy et al. (2001)	Expert knowledge; cost-driving factors; validation: comparison with cost data	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Salam et al. (2009)	Expert knowledge; decomposition of dev. process; cost-driving factors	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Scanlan et al. (2006)	Expert knowledge; cost-driving factors; validation: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; Jackknife technique
Siddique and Repphun (2001)	Expert knowledge; decomposition of dev. process; key role of IT system	Explicitly early phase	No mentioning of maintenance activities	Experience of employees; monte carlo simulation; fuzzy numbers	Internal data; emphasizes that limited data threats NPD cost estimation
Steck-Winter and Šebo (2008)	Expert knowledge; cost-driving factors; validation: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data
Sutopo et al. (2013)	Expert knowledge; cost-driving factors; key role of IT system; validation: comparison with cost data	Explicitly early phase	Regular adjustments	Unclear how to handle uncertainty	Internal data

Table 3: Overview of the findings of our systematic literature review – content analysis (continued)

Author (Year)	**Setup**	**Application**	**Maintenance**	**Uncertainty**	**Data**
Tyagi et al. (2015)	Cost-driving factors	Explicitly early phase	No mentioning of maintenance activities	Risk factors	Internal data
Wu et al. (2012)	Cost-driving factors; validation: comparison with cost data	No specific phase of application	No mentioning of maintenance activities	Rough sets	Internal data; emphasizes that limited data threats NPD cost estimation
Wu et al. (2015)	Cost-driving factors; validation: comparison with cost data	Explicitly early phase	No mentioning of maintenance activities	Unclear how to handle uncertainty	Internal data; emphasizes that limited data threats NPD cost estimation
Yin et al. (2015)	Cost-driving factors; validation: comparison with cost data; validation: comparison between methods	No specific phase of application	No mentioning of maintenance activities	Grey model and artificial neural networks	Grey model and artificial neural networks
Zhaodong et al. (2015)	Cost-driving factors; validation: comparison with cost data	Explicitly early phase	No mentioning of maintenance	Monte carlo simulation; equipment effectiveness index & interval number	Non-internal data; emphasizes that limited data threats NPD cost estimation

2.4 Results

In this chapter, we present the results of our literature review on NPD cost estimation. We start by giving a general overview about the body of literature before we dive in on the methods for NPD cost estimation that are described in the literature. Afterwards, we summarize several general aspects concerning practical challenges in NPD cost estimation: We start with guidelines to a successful setup, application, and maintenance of NPD cost estimation methods. Then we talk about the way methods deal with the challenge of uncertainty. We conclude this chapter with findings regarding the challenge of data availability in NPD cost estimation.

2.4.1 The body of literature on NPD cost estimation methods

In this section, we give a general overview of the publications analyzed for this literature review, based on the extensive data provided in Table 2.

2.4.1.1 NPD cost publication year analysis

Figure 5 shows the temporal distribution of our publications, clustered per decade. We observe that the topic gained relevance in the past two decades, as 33 out of 39 sources were published after the year 2000. This growth rate exceeds the regular growth of scientific journals according to Mabe (2003) and can be interpreted as growing interest of scholars in this particular topic. We want to highlight, that the topic was not completely neglected before. Although few publications picked up the topic of NPD cost estimation in a methodological manner, first scholars already saw its relevance for the long-term success of innovative organizations. The growing attention that the topic of NPD cost estimation triggered in the past decades emphasizes the demand for new solutions.

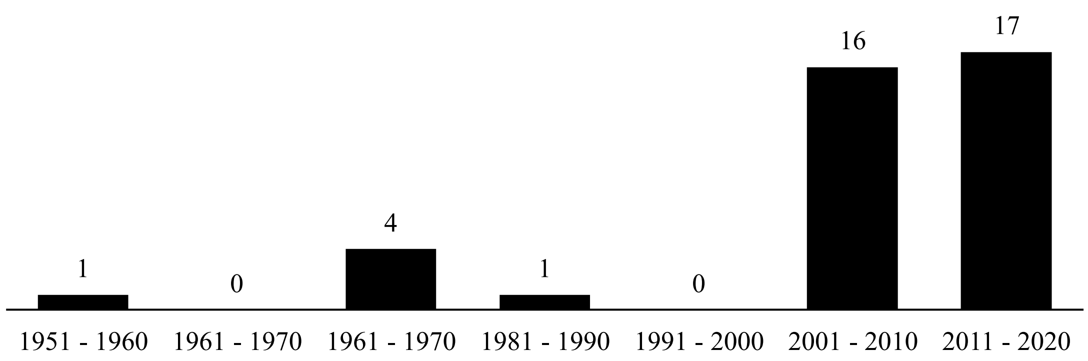

Figure 5: Publications in final set per decade

2.4.1.2 Literature discussing NPD cost estimation methods in NPD

Table 4 illustrates the publications clustered by our categories for literature streams and publication type. We also include the weighted average ranking per publication according to the SCImago Journal Rank 2018 for an assessment of the publications' relevance.[4]

[4] See Appendix A for a detailed overview of the publications in our final set summarized by literature stream, publication type, and rating.

Table 4: The final set of our literature review summarized by literature stream, publication type, and rating

Publications per literature stream and publication type	Number of publications	Publication rating[a]
Engineering	**28**	**0.47**
Book series	1	0.11
Conferences and proceedings	9	0.19
Contract research reports	1	not listed
Journals	17	0.61
Engineering & management	**3**	**0.83**
Journals	3	0.83
Management	**6**	**0.29**
Conferences and proceedings	1	not listed
Journals	5	0.29
Production	**2**	**2.05**
Journals	2	2.05
Overall	**39**	**0.58**

[a] average publication rating according to SCImago Journal Rank 2018

We can see that the topic of NPD cost estimation seems to be of primary interest in the *engineering* literature. Although several scholars published work in the fields of *management* and *production*, the vast majority of 31 out of 39 publications can be found in the *engineering* literature or at the *intersection between engineering and management*. This allows the conclusion that the problem of NPD cost estimation is one of high practical relevance for the people carrying out development activities.

While most of the research done was published in *journals*, the number of publications in the form of *conferences and proceedings* implies an active and feedback-driven discussion about this topic. To set the relevance and interest in this topic into proportion, we calculated the average publication ranking for our publications (if available), which is 0.58 according to the SCImago Journal Rank 2018. We further calculated the average rating of all 31,749 publications listed in the SCImago Journal Rank 2018 across all literature streams, which is 0.57. As both values are similar, we conclude that the literature in which this topic is discussed is of average interest.

2.4.1.3 Research approaches

In this chapter, we want to look at the type of research in which the NPD cost estimation methods are presented. We classify the 39 publications found by their research design. We differentiate between *conceptual* research and *empirical* research of different designs (*case study*, *simulation/experiment*), while respecting the fact that several sources present research with a conceptual as well as an empirical aspect. Figure 6 aims to illustrate this classification.

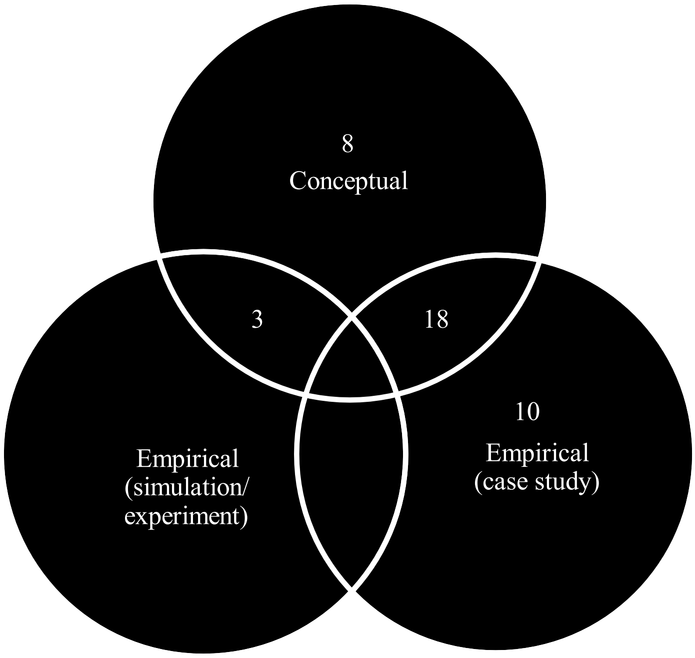

Figure 6: Numbers of publications in our final set clustered by (combinations of) research methods[5]

We can see that eight publications solely focus on the conceptual introduction of a method, while the vast majority rely on empirical data to either apply their proposed method or observe existing methods within the practice. As 28 sources rely on case studies in this context, we conclude this to be the dominant approach for research on NPD cost estimation methods. This seems appropriate considering the practical need for solutions, as the illustration in the context of actual cases was shown to contribute to our knowledge about phenomena in a unique way (Yin 2009). This underlines the practical impact and relevance of the NPD cost estimation problem in NPD.

Most of these studies use case studies either to gather data, confirm methodological approaches or observe what kind of methods are applied at certain companies. Little focus is set on case study research with the aim to understand how such an NPD cost estimation method functions in a practical environment. Such approaches could help emphasize practical issues in implementation and application.

2.4.1.4 Industries

New Product Development activities are carried out in nearly all industries that base their success on the launch of new and innovative products. To analyze the literature on NPD cost estimation methods for differentiation between these industries, Figure 7 shows the number of publications per industry.

[5] Example: 18 publications combine a conceptual part with an empirical case study approach.

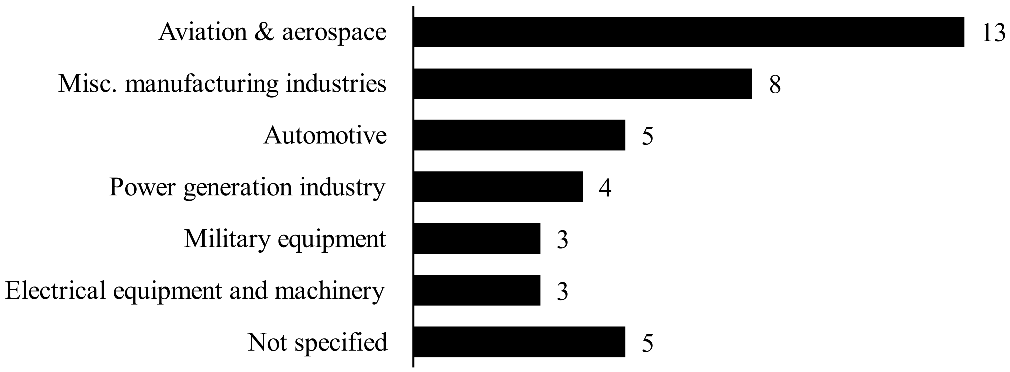

Figure 7: Numbers of publications in our final set per industry[6]

All industries represented have a focus on engineering activities and steadily develop products that have a claim to be innovative compared to their predecessors. This shows in heavy investments in NPD in those industries. The industry of Aviation & Aerospace is the most prominent example of such activities, since the development of an aircraft can easily cost several billion dollars (Bowen 2013).

Not all methods presented are specifically designed to function within that certain industry. While some authors, such as Carreyette (1977) or Chen (2020a) et al. illustrate rather industry-specific solutions, others such as Heller et al. (2012) or Wu et al. (2015) provide methods that are more a general concept that aims to be applicable to various environments. Overall, the industry analysis supports the need for NPD cost estimation methods in development-heavy industries.

2.4.2 Methods for NPD cost estimation

In this section, we take a deeper look at the NPD cost estimation techniques found in the literature. We start with an overview about the number of appearances of certain techniques before we introduce each of the techniques individually. We conclude with an analysis of the way techniques are applied in combination. The detailed classification of cost estimation techniques per publication can be found in Table 2.

2.4.2.1 Overview of cost estimation techniques applied for NPD costs

In Table 5 we show how often techniques are applied for NPD cost estimation purposes within our final set of publications. The following paragraphs aim to be a first impression as well as a guide for the following presentation of NPD cost estimation techniques. As described, we follow the classification scheme of Niazi et al. (2006), as shown in Figure 4. The techniques are clustered on several levels. On the first level, we distinguish between the groups of *qualitative techniques* and *quantitative techniques*. The second level of techniques distinguishes between the sub-groups of *intuitive techniques*, *analogical techniques*, *parametric methods*, and *analytical techniques*. On the third level, we distinguish between the actual cost estimation techniques, which resemble the lowest leaves in each branch of Figure 4. These techniques are *case-based techniques*, *expert systems*, *fuzzy logic systems*, *rule-based systems*, *regression analysis models*, *back-propagation neural network models*, *parametric methods*, *operation-based approaches*, *breakdown approaches*, *tolerance-based cost models*, *feature-based cost estimation*, *activity-based cost estimation*, and *target costing*. In Table 5 we further distinguish between the overall appearances

[6] As some publications cover more than one industry, for example by pursuing multiple case studies, the number adds up to more than the original 39 publications of our final set.

of certain techniques (columns two and three) and the appearance as a dominant method in the sense of the differentiation we explained in chapter 2.3.2 (columns four and five).

Table 5: Numbers and share of publications per technique in our final set

Technique	Publications including this technique	Share of publications including this technique	Publications including this technique as dominant[a]	Share of publications including this technique as dominant
Qualitative techniques	**25**	**64%**	**16**	**41%**
Intuitive techniques	***7***	***18%***	***2***	***5%***
Case-based techniques	3	8%	1	3%
Decision support techniques	6	15%	2	5%
Expert systems	*5*	*13%*	*2*	*5%*
Fuzzy logic systems	*1*	*3%*	*0*	*0%*
Rule-based systems	*0*	*0%*	*0*	*0%*
Analogical techniques	***20***	***51%***	***15***	***38%***
Regression analysis models	13	33%	8	21%
Back-propagation neural network models	9	23%	7	18%
Quantitative techniques	**28**	**72%**	**25**	**64%**
Parametric methods	***17***	***44%***	***15***	***38%***
Analytical techniques	***17***	***44%***	***10***	***26%***
Operation-based approaches	4	10%	0	0%
Breakdown approaches	4	10%	2	5%
Tolerance-based cost models	0	0%	0	0%
Feature-based cost estimation	8	21%	3	8%
Activity-based cost estimation	15	38%	5	13%
Target costing	1	3%	1	3%

[a] As two publications compare multiple dominant methods, the overall sum adds up to 41 instead of 39.

On the first level of technique classification, the overall appearance numbers show similar numbers for *qualitative* and *quantitative techniques*: both kinds of techniques are included in about two-thirds of the publications. When we look at the numbers for dominant methods on this level, we see that the ratio shifts towards *quantitative techniques*: 64% of the publications present a *quantitative technique* as dominant, while only 41% build on a dominant *qualitative technique*. Therefore, we suggest *quantitative techniques* to be particularly relevant as dominant approaches in the context of NPD cost estimation.

On the second level of technique classification, we see that only 18% of publications include *intuitive techniques*. I*ntuitive techniques* seem underrepresented in the application for NPD cost estimation compared to *analogical*, *parametric*, and *analytical methods*, which are all applied in more than 40% of the publications. Looking at the ratios among the dominant techniques, the low share of *intuitive techniques* remains similar. We could think of two reasons for this: First, intuitive techniques might occasionally lack objectivity. Considering that NPD costs represent heavy one-time investments early in the product development process, this can make them less relevant for this purpose. A second reason for the underrepresentation of intuitive approaches in our set might be of practical origin: the use of experts might implicitly be included or seen as a basic requirement by some approaches and is therefore not explicitly mentioned in all cases.

On the third level of technique classification, the overall appearance numbers allow us to identify the most relevant specific techniques for NPD cost estimation. The top five techniques for NPD cost estimation are *regression analysis models, back-propagation neural network models, parametric methods, feature-based cost estimation,* and *activity-based costing*. These five techniques all appear to be relevant in more than 20% of the analyzed publications, attesting their significance for methodological NPD cost estimation. Looking at the share among the dominant techniques, a similar picture remains relevant. Therefore, we identify these techniques as key approaches for NPD cost estimation. However, we observe that besides some techniques being more relevant than others, nearly all techniques listed by Niazi et al. (2006) are applied for NPD cost estimation. This broad set of techniques underlines the complexity of the problem that denies a single solution but can be approached from various perspectives.

2.4.2.2 Cost estimation techniques applied for NPD costs

In this section, we briefly describe the techniques that are applied for the estimation of NPD costs. We continue following the classification approach of Niazi et al. (2006), starting with *qualitative* and following with *quantitative techniques*.[7]

2.4.2.2.1 Qualitative techniques

Qualitative techniques are based on content-related and explicit comparisons between previous products and the new product. By adapting knowledge from similar past products, the estimator makes assumptions regarding the costs of future products. *Qualitative techniques* can be divided into *intuitive* and *analogical techniques*. While *intuitive techniques* rely more on expert knowledge and heuristics, *analogical techniques* make use of statistical instruments to uncover coherences to estimate costs.

2.4.2.2.1.1Intuitive techniques

Intuitive techniques use human judgement, typically based on experience from the past, to estimate the cost of future projects. The focus for these kinds of approaches lies in the efficient use of expert knowledge. *Intuitive techniques* can be divided into *case-based techniques and decision support techniques*.

Case-based techniques identify previous products that match the attributes of the new product to be estimated. The costs of these products are the basis for the estimation of the new product (Niazi et al. 2006). Harrold and Nicol (1977) emphasize that similarity is often the critical premise for the application of this technique. Although new projects often share similarities with previous products, in most cases a simple projection to future projects is not reasonable. Still, such an approach can be relevant for a first rough estimation. As a supplementary method, it often makes sense to rely on experience from past projects. Hinton and Moran (1983) propose such comparing analyses as input for certain aspects of their activity-based estimation approach, emphasizing that this “often forces the estimator to consider what will happen during the period of performance of the project” (Hinton and Moran 1983, p.3). These active evaluations of differences compared to previous projects are also a main aspect according to Niazi et al. (2006), who mention that this method is appropriate at the very early design stage, but relies on the availability of comparable projects.

Decision support systems help the estimators evaluate alternatives for the design of products to be developed. In contrast to *case-based techniques, decision-support systems* use stored knowledge not to

[7] See Figure 4 for an overview on all techniques according to the classification by Niazi et al. (2006).

identify single comparable products from the past, but to identify comparable alternatives in product attributes or processes and their corresponding costs. They aim to deliver comparable cost values on the different levels of an estimation process, for example, manufacturing or machining processes. Like this, decision-makers can build on degrees of freedom in a product's definition but also take restrictions into account when making an estimation. These systems can be split into systems that are *rule-based*, *fuzzy logic systems*, and *expert systems* (Niazi et al. 2006).

Rule-based systems are based on constraints regarding relevant product attributes or processes affecting the cost estimation. Within these constraints, cost-optimal attributes are identified among previous products. Like this, *rule-based systems* combine information attributes of previous products to deliver optimized cost estimation under restrictions. While the ambition to aim for economically optimal solutions seems beneficial, the approach can be very time-consuming in practice (Niazi et al. 2006). None of the publications in our final set applies a *rule-based system*.

Fuzzy-logic systems estimate product costs by defining product attributes and the resulting cost estimation as probability instead of a fixed value. Such *fuzzy logic systems* are particularly handy when applied in uncertain situations, as they allow to get more reliable estimates in such environments (Niazi et al. 2006). Aspects of a *fuzzy-logic system* are applied once in the work of Relich (2016), combining *fuzzy-logic* with neural network methods to identify relationships between the NPD costs and a products' features.

Expert systems build on mimicking the cost estimation capabilities of experts through databases. By storing relevant cost and product experience in a concise system, estimations can be made in a more efficient way than through individual interaction. *Expert systems* play a significant role in several publications covering NPD cost estimation methods, although only few times as dominant method and more often as supplementing technique. As this approach is based on storing expertise in a database for later use, it does not surprise that such aspects are relevant for various approaches in NPD cost estimation (Niazi et al. 2006). Several authors emphasize that expert knowledge plays a crucial roles when it comes to the estimation of NPD costs (Case 1972; Harrold and Nicol 1977; Hinton and Moran 1983; Holtta-Otto and Magee 2006; Lambert and Sackett 1959).

2.4.2.2.1.2Analogical techniques

Analogical techniques are based on the idea that similarities between the cost data of previous and future projects can be expressed by quantitative relationships. The two techniques that are mentioned in this regard by Niazi et al. (Niazi et al. 2006) are *regression analysis models* and *back propagation neural network models* (hereinafter *BPNN*).

Regression analysis models establish a relationship between historical data and specific characteristics or variables of the corresponding cost objects. The most common type of such a relationship is linear, making linear regression models the most relevant regression-based technique for cost estimation approaches. A multiple linear regression model is set up to estimate the value of one dependent variable on the right side of the equation by several explanatory variables or regressors on the left side. The regressor vector multiplied by the parameter values of a specific estimation case plus an error variable aims to estimate the dependent variable. Such models are often fitted using methods such as the least-squares approach to find the most significant and explaining model between the variables. Formula 1 shows the general notion of a linear regression model with the observed values to explain y_i, the intercept term β_0, the parameters β_i, the independent variables or regressors x_i and the error variable ε_i (Freedman 2005).

$$y = \beta_0 + \beta_1 x_1 + \ldots \beta_n x_n + \varepsilon \quad (1)$$

Formula 1: Generic equation of a linear regression model

In NPD cost estimation, *regression analysis models* are one of the most applied techniques. Within these applications, various parameters are used for the estimation of NPD costs. As an example, Bashir and Thomson (2004) estimate design time by a function of product complexity, the ratio of technical difficulty and team expertise, the type of drawings submitted to the customer, and the involvement of design partners. As Bashir and Thomson (2001) emphasize in a previous work, the development of such a model requires a careful selection of parameters: To keep model complexity reasonable, only the most relevant variables should be included, depending on the specific case. This also shows in other publications, as each model proposes a different set of independent variables influencing the NPD costs. A common theme though is the inclusion of factors that focus on features, specifications, and processes within development activities for a new product. Zhaodong et al. (2015) propose for instance variables such as maximum flight speed, weight, or an efficiency index for their model estimating the development costs of aviation equipment. Other scholars propose a similar combination of regressors in dependence of the object in estimation (Johnson and Kirchain 2011; Large et al. 1976; Li et al. 2009). Salam et al. (2009) propose the application of the jackknife technique to efficiently determine the regression coefficients more efficiently.

Back-propagation neural networks (*BPNNs*) aim to explain relations between variables by building on a concept similar to the human brain. Such a *BPNN* consists of a collection of nodes that are usually clustered in layers. Each of these nodes transforms incoming data following a certain function and forwards that information to the next relevant node. Like this, the variables are transformed from the first layer of nodes, the so-called input layer, to the last one, the so-called output layer. The layers in between are called hidden layers (Hopfield 1988). Like this, *BPNNs* allow finding connections between variables in an explorative way, making them particularly useful for unclear relationships of cost factors (Niazi et al. 2006). Figure 8 illustrates a multilayered *BPNN* (Abraham 2005).

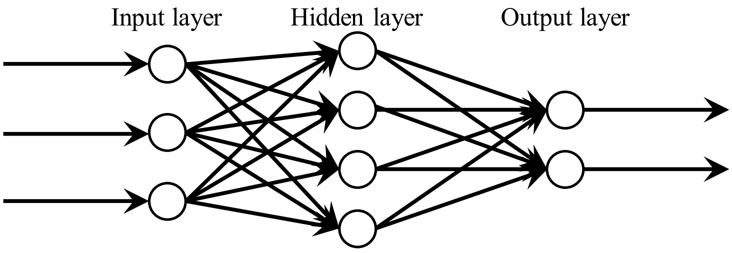

Figure 8: Illustration of a multilayered BPNN (Abraham 2005)

BPNNs are the third most applied technique within the NPD cost estimation methods found in the literature. Since it is also considered a dominant technique in most of these applications, *BPNNs* are highly relevant for NPD cost estimation purposes. Of special interest in this context is their ability to deal with nonlinear problems and their strong fault tolerances (Mousavi et al. 2015; Wu et al. 2012; Yin et al. 2015). Their ability to identify relations between variables is a major advantage (Relich 2016; Wu et al. 2012). In combination with supporting techniques such as grey systems in the case of Yin et al., fuzzy neural systems, or others, these abilities can be improved for overall increased efficiency in NPD cost estimation (Chen et al. 2020a; Deng and Yeh 2010; Relich 2016; Wu et al. 2012; Yin et al. 2015).

2.4.2.2.2 Quantitative techniques

Quantitative techniques are usually based on the detailed analysis of the products' characteristics. Based on these characteristics, the estimation is calculated following a certain logic of products' design features, process details, or other parameters. Therefore, *quantitative techniques* go beyond the analysis of historical product cost data and can be differentiated in *parametric methods* and *analytical techniques*.

2.4.2.2.2.1Parametric methods

Parametric methods follow the idea to express costs as a function of its constituent variables. When the parameters, that drive the cost can easily be identified, this technique can be a very effective tool (Niazi et al. 2006). In difference to *regression analysis models* that follow a similar approach, the impact of cost drivers in *parametric methods* does not exclusively need to build on data from comparable previous projects. Therefore, it deals better with new cost drivers or changes in the influence of cost drivers for example through technical innovations. Within our final set of methods for NPD cost estimation, *parametric methods* are the most applied class of techniques. This applies to the overall application as well to appearances as dominant techniques. According to Qian and Ben-Arieh (2008), *parametric methods* are of special relevance for this purpose, since it is applicable in the early design phase when few details are known yet. Product characteristics are often set in relation to the NPD costs by using historical data to discover patterns and relationships. To identify these relationships, data usually has to be prepared for effects such as inflation or learning curves (Scanlan et al. 2006). However, besides insights from the past, *parametric methods* allow the inclusion of cost drivers that might not have been relevant for previous projects but gain significance in the future.

In general, the setup of a *parametric method* follows four steps, as described by Heller et al. (2012): First, the parameters must be defined, and the relevant data prepared. Afterwards, the functions of the parameters have to be determined, and the effects of these parameters on the costs are specified. Supplementing methods such as cluster analysis, *regression analysis models* or aspects *of activity-based costing* based on activities within the development process can be beneficial for the identification of the relevant cost drivers (Chwastyk and Kołosowski 2014; Qian and Ben-Arieh 2008; Salam et al. 2009). Defining these cost drivers is an essential task within this technique, and should be done with the help of experts, that are able to identify them for the specific development environment the method is applied in (Bashir and Thomson 2004). Therefore, the factors for such models will vary depending on the application case. While Salam et al. (2009) define the type of design, the degree of change, concurrency, and the experience of the personnel as relevant parameters for estimating the development cost of compressors, Chwastyk and Kolosowski (2014) build on the diameter of the valves to be developed, as the most important parameter. The numerous applications we could find in the literature for *parametric methods* in NPD cost estimation emphasize the outstanding relevance in this matter.

2.4.2.2.2.2Analytical techniques

Analytical approaches aim to estimate costs by constructing them as the sum of all relevant cost objects. To do this, a development project must be decomposed. This decomposition can follow different logics like technical components or main activities of the development process (Niazi et al. 2006). Within NPD cost estimation, *analytical techniques* play an important role, as almost every other publication includes such approaches. As only about half of them is applied as dominant technique though, we see that such approaches are often used as supplementing techniques. There are different kinds of *analytical techniques* which we will introduce in the following. Although the distinction between techniques is sometimes blurry, we adapt the logic of Niazi et al. to differentiate them (Niazi et al. 2006). We start with *operation-based* approaches and *breakdown approaches* before we follow with *tolerance-based models*. Afterwards, we will continue with *feature-based cost estimation* and *activity-based costing* before we conclude with techniques incorporating *target costing* aspects.

While the *operation-based* approach is applied by summing up estimations for all major operations focusing on the time performing operations, nonproductive time, and setup times, *breakdown approaches* are based on decomposition along all the various cost types involved in the overall process (Niazi et al. 2006). Both approaches are applied for NPD cost estimation in four publications within our final set. While the operation-based approach is exclusively mentioned as a supplementary technique, half of the appearances of the breakdown approach are as dominant method. Holtta-Otto and Magee (2006) apply such an approach by presenting a three-level breakdown structure starting with the project, task groups, and then single tasks.

Tolerance-based models are set up to "estimate product cost considering design tolerances of a product as a function of the product cost" (Niazi et al. 2006, p.568). Therefore, such approaches set optimal design parameters to achieve certain product costs. None of the publications regarding NPD cost estimation incorporates such an approach.

Feature-based cost estimation is applied in about every fifth publication that we found. Less than half of these apply this technique as dominant. *Feature-based cost estimation* aims to identify features of a product that are in relation to the product's costs. In difference to *regression analysis models* or *parametric methods*, in which no general classification between parameters is made, feat*ure-based cost estimation* clearly differentiates between design-related features (for example materials used) and process-oriented features (for example particular molding process required). This allows the simple identification of cost structures within a product (Niazi et al. 2006). For their NPD cost estimation of airframes, Roy et al. (2001) include quantitative design features like the number of holes as well as process-oriented features such as the experience of the engineers involved. Another example for the successful application of feature-based cost estimation for NPD cost is the work of Chen et al. (2010), who include typical design features such as the number of parts and their relationships as well as more function-driven design aspects as the number of performances and constraints.

Activity-based cost costing (hereinafter *ABC*) estimates the total cost by identifying all direct and indirect activities necessary to complete the task. In difference to the similar *operation-based approaches or breakdown approaches*, *ABC* looks at the product more holistically by also incorporating activities that are not directly but indirectly related to the product development process (for example project management). These activities are then estimated in their cost and quantity and summed up to the resulting overall NPD costs.

ABC is the most counted technique in our final set in general but is only mentioned as a dominant technique in one-third of those applications. While Qian and Ben-Arieh (2008) link *activity-based costing* aspects with a *parametric method* in their approach to estimate the design and development costs of machined rotational parts, Siddique and Repphun (2001) solely set on this approach in their method to estimate costs for the development of hard disk drive spindle motor platform. Other publications also include similar approaches either as a dominant technique or as supplementing approach (Lambert and Sackett 1959; Liu et al. 2013). While some approaches build on broad activities such as general engineering activities in man-years (Carreyette 1977; Lambert and Sackett 1959), others build on rather sophisticated catalogues of activities and estimations for them (Steck-Winter and Šebo 2008). Unifying in all applications, authors agree that historical knowledge about projects and processes in development is crucial for successful implementation (Holtta-Otto and Magee 2006; Lambert and Sackett 1959).

Although *target costing* is not considered as a cost estimation method in the classification of Niazi et al. we decided to include this as a separate technique, since Riedrich and Sasse (2005) introduce such a solution. Their combination of earned value method and *target costing* allows estimating the development costs of a product with respect to its overall business case. With their work, they incorporate a perspective on development cost in the *target costing* methodology, which was widely neglected before.

2.4.2.3 Combination of techniques for NPD cost estimation

As shown in Table 2, most publications in our final set combine aspects of several cost estimation methods to develop efficient approaches for NPD cost estimation. Others illustrate methods that only rely on a single technique, while few illustrate several methods in a comparing way. Figure 9 illustrates the share among our final set of publications. In this section, we talk about how techniques are combined for NPD cost estimation purposes.

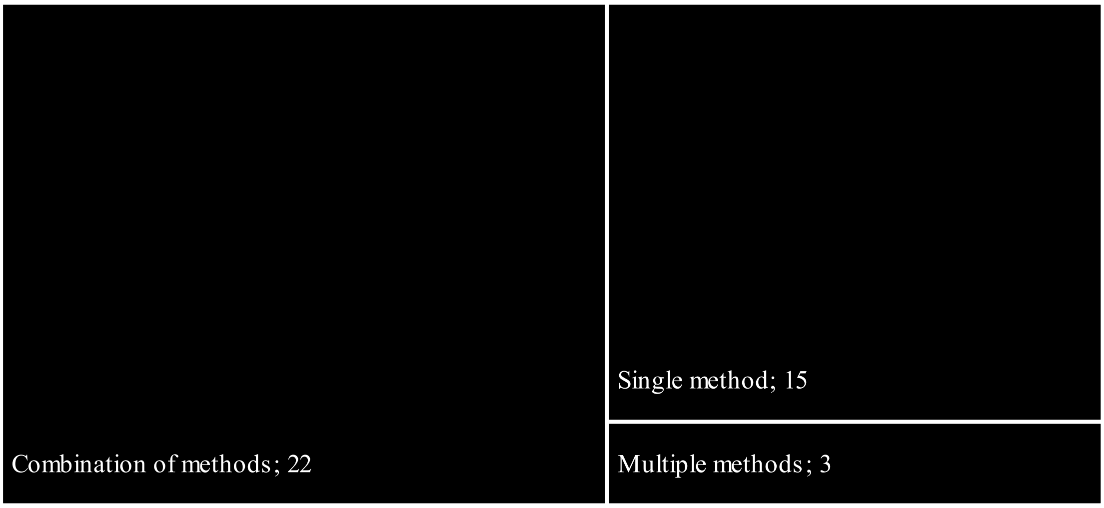

Figure 9: NPD cost estimation methods in the context of their combination status within our final set[8]

Most of the approaches for NPD cost estimation combine several techniques. Niazi et al. (2006) support the fact, that such a combination of techniques is often necessary to achieve a more efficient and accurate cost estimation. To understand how this is applied in NPD cost estimation, we conducted an analysis investigating how specific techniques are combined. Some publications combine more than two techniques. However, we analyze the combinations within our final set by looking at the techniques in pairs, as this includes most of the information and allows a simpler visualization. Table 6 illustrates that analysis. The number left of the vertical bar in each cell shows how often the technique in that column and row are applied in combination. The second number on the right side of the vertical bar shows how often the dominant method in each row is supplemented by the technique in the respective column. We identified four combinations that are highlighted bold and underlined in the table as most common, either because the combination of techniques appears at least six times overall or the combination appears at least three times as a combination of dominant and supplementing techniques. In the remainder of this section, we summarize how these combinations are applied for NPD cost estimation.

[8] As one publication compares multiple methods which by themselves are combination of techniques, the overall sum adds up to 40 instead of 39.

Table 6: Numerical overview of the combination of techniques for NPD cost estimation

<table>
<tr><th>Number of technique-appearances in combination

(number of overall combinations | number of dominant-supplementing combinations)[a,b]</th><th>Case-based techniques</th><th>Expert systems</th><th>Fuzzy logic systems</th><th>Rule-based systems</th><th>Regression analysis models</th><th>Back-propagation NNs</th><th>Parametric methods</th><th>Operation-based approaches</th><th>Breakdown approaches</th><th>Tolerance-based cost models</th><th>Feature-based cost estimation</th><th>Activity-based costing</th><th>Target costing</th></tr>
<tr><td>Case-based techniques</td><td></td><td>1|-</td><td></td><td></td><td></td><td></td><td>1|-</td><td></td><td></td><td></td><td></td><td>1|-</td><td></td></tr>
<tr><td>Expert systems</td><td>1|-</td><td></td><td></td><td></td><td></td><td></td><td></td><td>1|-</td><td>2|-</td><td></td><td>1|-</td><td>2|-</td><td></td></tr>
<tr><td>Fuzzy logic systems</td><td></td><td></td><td></td><td></td><td></td><td>1|-</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Rule-based systems</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Regression analysis models</td><td></td><td></td><td></td><td></td><td></td><td>2|1</td><td><u>6|1</u></td><td></td><td></td><td></td><td>1|1</td><td>2|2</td><td></td></tr>
<tr><td>Back-propagation NNs</td><td></td><td></td><td>1|1</td><td></td><td>2|-</td><td></td><td>2|1</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Parametric methods</td><td>1|1</td><td></td><td></td><td></td><td><u>6|5</u></td><td>2|1</td><td></td><td>1|1</td><td></td><td></td><td><u>3|3</u></td><td><u>6|5</u></td><td></td></tr>
<tr><td>Operation-based approaches</td><td></td><td>1|-</td><td></td><td></td><td></td><td></td><td>1|-</td><td></td><td>2|-</td><td></td><td>4|-</td><td>4|-</td><td></td></tr>
<tr><td>Breakdown approaches</td><td></td><td>2|1</td><td></td><td></td><td></td><td></td><td></td><td>2|-</td><td></td><td></td><td>2|-</td><td>2|-</td><td></td></tr>
<tr><td>Tolerance-based cost models</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Feature-based cost estimation</td><td></td><td>1|1</td><td></td><td></td><td>1|-</td><td></td><td><u>3|-</u></td><td>4|2</td><td>2|2</td><td></td><td></td><td><u>8|3</u></td><td></td></tr>
<tr><td>Activity-based costing</td><td>1|1</td><td>2|1</td><td></td><td></td><td>2|-</td><td></td><td><u>6|-</u></td><td>4|1</td><td>2|-</td><td></td><td><u>8|1</u></td><td></td><td></td></tr>
<tr><td>Target costing</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

[a] *Remark*: The number left of the vertical bar represents how often the technique in the row and the technique in the column appear in combination, the number right of the vertical bar represents how often the method in the row is a dominant method and combined with the method in the column. We identified the cells that are highlighted bold and underlined as most common combinations, either because the combination of techniques appears at least six times overall or the combination appears at least three times as a dominant-supplementing combination.

[b] *Example*: The cell in the row *regression analysis models* and *parametric methods* shows a value of 6|1. This means that these two methods appear combined in six publications. In one of these publications, regression analysis is the dominant method.

2.4.2.3.1 Feature-based cost estimation and activity-based costing

In eight approaches for NPD cost estimation, *feature-based cost estimation* is combined with *activity-based costing*. This makes it the most common combination. In three cases, the dominant method is a *feature-based* technique, while *ABC* appears to be dominant in one case. In the other approaches in which these two methods are combined, they both appear as supplementing techniques.

Chen et al. (2010) present an approach to determine the relative design cost of alternative product architectures. They build on the multiple features mapping theory to support development decision-making. While most of the features they include for their approach are based on the distinct features of the design alternatives, others such as the number of solutions that designers are working on, are dependent on the activity level of each estimation object. They illustrate their approach by applying it for the development cost estimation of single-use cameras. Holtta-Otto and Magee (2006) pursue a similar approach as they set up their project-complexity framework, which mainly consists of product features such as artifact complexity or design problem complexity, but also includes factors regarding process complexity such as the number of design tasks. The approach of Braun and Lindemann (2007) is based on a four-layer concept which allows a systematical process of estimating development cost by defining resources necessary as a result of dependencies between those four layers. In their approach, the functions per product are defined in the first layer, before they are transferred to physical requirements on the second one. The third layer translates these to processes while the corresponding resources are defined on the last level. The resources are defined by cost functions depending on the number and types of process steps necessary to develop the defined product. Roy et al. (2001) as well as Scanlan et al. (2006) present approaches in which the techniques of *feature-based cost estimation* and *ABC* both appear as supplementing techniques. Roy et al. (2001) apply a *regression analysis model* within their case study at a large European aerospace manufacturer that includes quantitative as well as qualitative design inputs for their model. To set it up, features of the product, as well as certain engineering activities, are estimated. Scanlan et al. (2006) similarly propose a *parametric method* at their DATUM project at Rolls-Royce which aims to support aerospace design decision making. By building on a cost library for specific features of products as well as development activities and their effect on design cost, they combine aspects of *feature-based* cost estimation as well as *activity-based costing*.

The combination of *feature-based cost estimation* and *ABC* is of high relevance for the estimation of NPD costs. This is not surprising, as many stakeholders are involved in the development of a product, which makes the aspect of processes or activities highly relevant. As the object that is in development and its features only partly respect the aspects of processual product development, it seems reasonable to combine these two techniques.

2.4.2.3.2 Parametric methods and regression models

In six of the publications, *parametric methods* are combined with *regression analysis models*. In five of these approaches, *parametric methods* are dominant, while a *regression analysis model* is dominant in one of them. Combining *these two techniques* to set up an approach that efficiently estimates NPD costs seems intuitive, as the regression enables to define quantitative relations between parameter levels and the cost of a development project.

Bashir and Thomson (2004) implement such an approach they propose in the context of designing hydroelectric generators. After defining the most relevant parameters and their possible levels with experts, they apply a *regression analysis model* to estimate their impact on the NPD costs, based on previous development projects. Similar, the same authors set up another model which they tested in two Canadian companies. In that case, they put special attention on the functional definition of the parameters such as the product complexity (Bashir and Thomson 2001). Li et al. (2009) propose the described combination for the NPD cost estimation of armored vehicles. To support the selection of the right parameters and to deal with the issue of small data samples, Chen et al. (2019) apply a P-value analysis as well as gray correlation analysis in their *parametric method* for the NPD cost estimation of general aviation aircraft projects. After they conduct a principal component analysis, they apply these methods and continue by setting up a corresponding *regression analysis model*. To validate their approach in terms of accuracy, they successfully compare it to a *back-propagation neural network*. Salam et al. (2009) also base their *parametric approach* on a *regression model* and include a sensitivity analysis to identify relevant variables influencing the NPD cost.

The combination of *parametric approaches* with *regression analysis models* seems rather intuitive, as it allows to combine comparisons to previous projects without neglecting adjustments for future developments. Several authors show how such methods were successfully implemented for NPD cost estimation purposes. Furthermore, supporting statistical tools are applied to improve the validity of such models.

2.4.2.3.3 Parametric methods and activity-based costing

The synergy between *parametric methods* and *activity-based costing* is the next combination of techniques that is of special importance for the estimation of NPD costs. Such combinations appear in six of our publications with the *parametric method* being the dominant method in five of them. None of the publications mention *ABC* as the dominant method in this regard, making it a main supplementing technique for *parametric models*.

Carreyette (1977) proposes an application for merchant ships in the very early phase of design. While project-specific parameters such as size, weights, powering, or capacity are set as relevant factors in this approach, the transfer to development costs of a project is made by combining the levels for these parameters with the costs of man-hours required to fulfill the corresponding development activities. This inclusion of man-hour rates as driver rates for the estimation of NPD costs is a common way and seems reasonable, considering the relevance of engineering work in product development. Qian and Ben-Arieh (2008), as well as Scanlan et al. (2006), follow the same approach in their methods for NPD cost estimation of machined rotational parts respectively civil gas turbine engines. Steck-Winter and Šebo (2008), as well as Sutopo et al. (2013), emphasize the need for a cost library, as information regarding activity-driver rates is necessary to include *activity-based costing* in such parametric methods.

Aspects of *activity-based costing* are common in *parametric methods* for NPD cost estimation. Due to the importance of engineering activities, the link between man-hours and costs of a development project through this synergetic approach proves to be beneficial.

2.4.2.3.4 Parametric methods and feature-based cost estimation

Parametric approaches are often supplemented by *feature-based cost estimation*. Three of the publications mentioned in the last section also include such *feature-based* components in their *parametric methods*, making this a valid combination.

While Carreyette (1977) includes features such as a product's weight for the development cost estimation of merchant ships, Scanlan et al. (2006) use product features like the width or length as important parameters for estimation of the development costs of aircraft. Sutopo et al. (2013) go a step further and also include parameters like the type of raw materials used for a product as input values for their model. The broader reason for the influence of such parameters is brought forward in the work of Holtta-Otto and Magee (2006), as they define measurements of product complexity as the most significant features within their general approach for NPD cost estimation.

Scholars show that *parametric methods* for NPD cost estimation are commonly supplemented not only by aspects of *ABC* but also *feature-based cost estimation*. Both techniques function as efficient ways to supplement the setup of a *parametric method*.

2.4.3 Guidelines to the successful setup, application, and maintenance of an NPD cost estimation method

The techniques that can be applied to estimate NPD costs are of varying nature. Still, most methods incorporate three steps for a sustainable estimation process: *setup*, *application*, and *maintenance*. In the following, we summarize the most relevant guidelines regarding these steps, according to the literature. Figure 10 illustrates the most aspects described in this section. As described in chapter 2.3.2, we present the detailed information per publication in Table 3.

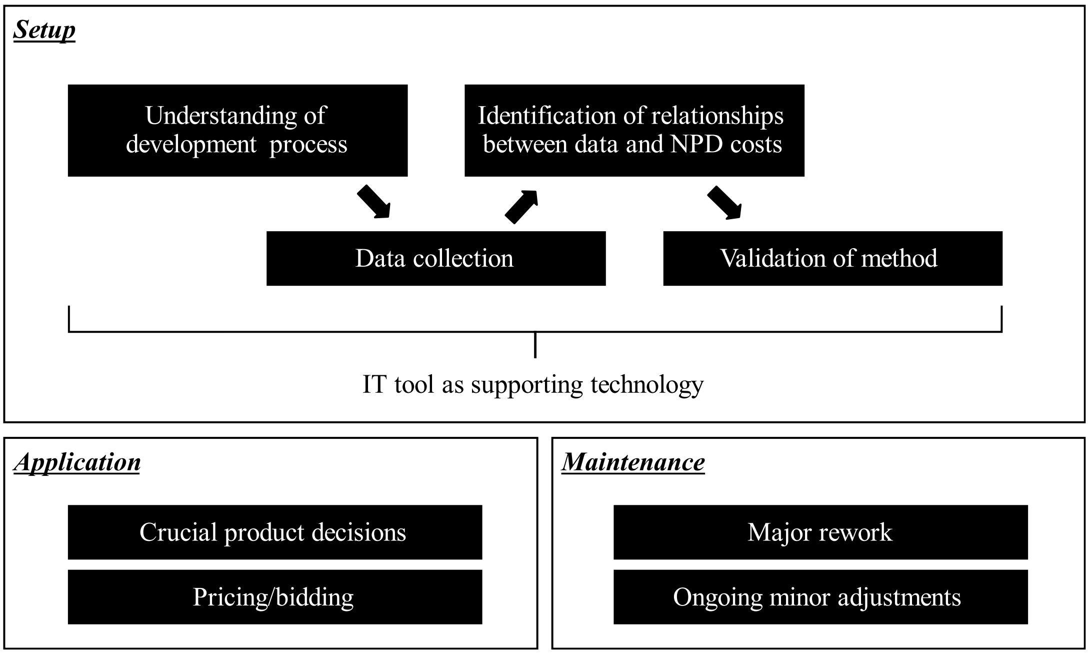

Figure 10: Overview of relevant aspects regarding setup, application, and maintenance in NPD cost estimation methods

2.4.3.1 Setup of an NPD cost estimation method

There are four general steps for the successful setup of an NPD cost estimation method. The first step is to understand the process of product development in the specific environment of the company (Roy et al. 2001). Building on that, relevant data should be collected as a second step (Adelberger and Haft-Zboril 2015; Bashir et al. 2006; Roy et al. 2001). Afterwards, that data should be used to develop a relationship between product data and the NPD cost of a product. As the last step, a validation analysis should be pursued to make sure the model is functional (Adelberger and Haft-Zboril 2015; Gebhardt 2017; Roy et al. 2001). In the following paragraphs, we summarize relevant aspects regarding these four steps as well as emphasize on the use of an IT tool as supporting technology.

The first step is to get a deep understanding of the development process in the environment the method is to be applied. To achieve a sufficient understanding of the development process, it is crucial to include the right people in the setup process. As development processes are highly complex and the drivers of NPD costs are often not obvious, the world of cost management, as well as the area of engineering, have to come together (Holtta-Otto and Magee 2006). Only with such a multidisciplinary approach, a model for this purpose can achieve a sufficient level of validity in practice (Adelberger and Haft-Zboril 2015; Roy et al. 2001; Scanlan et al. 2006). However, a company should be aware of the potential biases of people involved in such activities (Case 1972).

In most setup scenarios it is necessary to decompose the development process into smaller aspects to set up an estimation model. For this purpose, Scanlan et al. (2006, p.1026) propose a hierarchical structure which "forces users to decompose a problem into a logical series of steps". Such a decomposition can be done based on a more process-related structure through the development process, as Riedrich and Sasse (2005) or Liu et al. (2013) propose, but can also incorporate technical aspects such as components or technical elements of the product (Harrold and Nicol 1977; Holtta-Otto and Magee 2006).

The second setup step of data collection is especially challenging in NPD cost estimation. In most cases, a company's cost- and product databases are the starting point for the setup of a method (Chen et al.

2020b; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). Roy et al. (2001) argue that as much data as possible should be included for NPD cost estimation. Due to the innovative character of NPD, the identification of comparable data can be challenging, and often assumptions must be made to transfer available data to the future (Harrold and Nicol 1977; Roy et al. 2001). Few authors do not rely on data sources from inside the company, but rather build on public databases or data-independent cost estimation measures (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b).[9]

The third step of a method's setup is the identification of relationships between product information and NPD cost. Although not all techniques are of parametric nature, the definition of processes, features, or other kinds of cost drivers is a common motive. Several tools are proposed to aid in the definition of these cost drivers. In their regression analysis model, Yin et al. (2015) propose a stepwise procedure for the inclusion of statistically relevant parameters only. Mousavi et al. (2015) search for the optimal parameter combination with the help of a grid-search algorithm together with the cross-validation method. A visual approach for this task is taken by Qian and Ben-Arieh (2008), as they model design activities with the help of diagrams to identify relevant activity-related drivers of NPD costs. Of special importance for the definition of cost drivers is the challenge to avoid interdependencies among them, as this might conceptionally endanger a sufficient estimation result (Case 1972).

The cost drivers that are relevant for a certain setting highly depend on the product and the development situation an approach is designed for. A holistic list of relevant cost drivers for NPD cost estimation can therefore not be given. Still, four classes of cost drivers are recurring in the methods available in the literature. First, the aspect of product complexity is included in several publications (Steck-Winter and Šebo 2008; Tyagi et al. 2015). As this factor influences the challenges during development, it is used as driver in various shapes. The second large cluster of cost drivers is closely related to the development process itself: the activities and resources required for product development appear as a recurring factor for NPD cost in several approaches (Bashir and Thomson 2001; Siddique and Repphun 2001). The third class of cost drivers is more tangible: the aspect of measurable component features such as size or weight (Chen et al. 2019; Johnson and Kirchain 2011). The last class of cost drivers represents human factors. Bashir and Thomson (2001) propose the skill, experience, and attitude of team members as a major contributor to variation in product development cost.

The fourth and last step of setting up an NPD cost estimation method is a successful validation. The goal is to show and make sure, that the model performs efficiently, and its estimations are reliable (Adelberger and Haft-Zboril 2015; Hamilton and Westney 2002; Yin et al. 2015). The most common way to test a newly set up method for NPD cost estimation is to estimate costs for previous projects with it. Bashir et al. (2006) do this by splitting historical cost data into training and testing samples, while Bashir and Thomson (2004) test whether the estimations of their model lies within 25% deviation compared to the actual values. In some cases, a comparison between different models can be of additional value: Chen et al. (2020b) compare the accuracy of their back-propagation neural network with a comparable linear regression model for this purpose.

A supporting IT tool plays an important role in the setup of many NPD cost estimation methods. Such an IT tool must be developed during the setup phase to efficiently apply the method later. Relich (2016, p.23) emphasizes that such a system can "improve the capacity of information management systems used in modern designing and manufacturing". As most techniques depend on efficient information management, such a solution can be a necessity for the application (Johnson and Kirchain 2011). Sutopo et al. (2013), as well as Bashir and Thomson (2004) further underline the importance of a user-friendly design, for a quick and easy operation by users.

[9] We talk more comprehensively about the challenge of data availability in chapter 2.4.5.

2.4.3.2 Application of an NPD cost estimation method

We could identify two relevant application cases for NPD cost estimation methods in the literature: the support of crucial product decision-making and pricing and bidding purposes.

The major application scenario of an NPD cost estimation method is to support decision-making in the early phase of NPD. As the NPD costs are usually the first cost type to occur within a new product development project, the application of an NPD cost estimation method usually falls in the early phase of a product's life (Chen et al. 2010; Johnson and Kirchain 2011). In this product phase, crucial decisions about the product are made. A consistent cost estimation method in this phase enables a company to make such decisions in an efficient manner (Adelberger and Haft-Zboril 2015). Typically, such analyses cover the judgement about the financial feasibility of a product or build the analysis for future resource plans (Hinton and Moran 1983; Holtta-Otto and Magee 2006; Li et al. 2009; Riedrich and Sasse 2005). Comparing alternative solutions or designs for a product is another important reason to estimate the NPD cost of a new product in this phase (Carreyette 1977; Qian and Ben-Arieh 2008; Scanlan et al. 2006).

A second application scenario of an NPD cost estimation method is the incorporation for pricing or bidding purposes. This is of special relevance for contract-developing companies, as they need to make sure that they offer their services at a competitive but also economically reasonable price. Sutopo et al. (2013) present this purpose in their work regarding bidding strategies for contract-development companies.

2.4.3.3 Maintenance of an NPD cost estimation method

Most NPD cost estimation methods are not designed to remain untouched until eternity, but rather must be put under regular maintenance. As most techniques build on data from previous projects, a regular update becomes necessary: As time goes by, new development projects will provide new data that should be incorporated in the respective method (Bashir et al. 2006; Heller et al. 2012). The agility of product development also frequently leads to changes in the development process itself. Such changes often have an impact on a product's NPD cost structure and should therefore also trigger an adjustment of the corresponding estimation method (Johnson and Kirchain 2011).

Maintaining an NPD cost estimation method does not necessarily require to completely setup a method every time new data arises, or the development process changes. More often, minor changes of a method's components will be sufficient (Adelberger and Haft-Zboril 2015). No general guideline can be given regarding the timing of such maintenance activities. An evaluation between the effort of adjusting the method and the gain of accuracy or credibility should be the leading measure. Johnson and Kirchrain (2011) propose a complete rework of their method every two to three years while Adelberger and Haft-Zboril (2015) suggest such activities after three to five years. Heller et al. (2012) add, that a continuous process of maintenance is the key to keeping a model credible as a crucial component of product development.

2.4.4 Dealing with uncertainty in the context of NPD cost estimation

Several authors suggest that a high level of uncertainty is critical for NPD cost estimation (Harrold and Nicol 1977; Mousavi et al. 2015; Zhaodong et al. 2015). Neglecting these uncertainties endangers an objective estimation of NPD cost (Chwastyk and Kołosowski 2014). Uncertainties in the context of NPD can take different shapes: While Tu and Xie (2003) for example emphasize that physical aspects such as a product's geometry can be uncertain, Salam et al. (2009) suggest that product complexity, in general, is subject to a high level of uncertainty during the project.

As described in chapter 2.3.2, we analyzed our publications to find relevant approaches to face the challenge of uncertainty in NPD cost estimation. Detailed information can be found in Table 3. We differentiate the insights of our analysis in *experience-based approaches* and *mathematical approaches*.

We classify *experience-based approaches* as concepts that mostly build on human experience to face uncertainty in NPD cost estimation. The experience of employees can be an efficient answer to uncertainty. Lambert and Sacket (1959) put this into context as they suggest the experience of engineers to be the most relevant source for reliable information when preparing bid estimates in their study in an engineer-to-order environment. Similar, Hinton and Moran (1983) describe the iterative process of risk evaluation under the inclusion of experts as a direct influence of the cost estimate. Relying on such experts to estimate uncertain outcomes is an efficient and simple way of dealing with the topic of uncertainty. However, it lacks objectivity from a methodological point of view.

Mathematical approaches to face uncertainty in NPD cost estimation build on statistical techniques that deal with unsure expectations towards the future. Proposed mathematical approaches to face uncertainties in NPD cost estimation are monte carlo simulation, fuzzy numbers, and the use of interval numbers. Zhaodong et al. (2015) apply monte carlo simulation in their model to estimate NPD costs for aviation equipment to face uncertainties in a product's design. Similar, Siddique and Repphun (2001) build on a monte carlo simulation to cover uncertainties associated with activities in hard disk drive spindle motor development. By applying this technique, many possible values for certain project characteristics can be included in the NPD cost estimation method. The fuzzy numbers approach aims for a similar solution: By not setting a single value for a variable, but rather a connected set of possible values weighted between zero and one, this technique allows to incorporate uncertainties into a model (Dijkman et al. 1983; Siddique and Repphun 2001). Zhaodong et al. (2015, p.144) further emphasize the fact that sometimes relying on "single numerical variables will lead to loss of information". Therefore, they propose the adaption of interval numbers for values in NPD cost estimation methods to be a valuable addition for an advantageous inclusion of uncertain aspects.

The tools presented for dealing with uncertainty in NPD show the relevance for NPD cost estimation. However, surprisingly few scholars actively incorporate such measures to tackle this major challenge. Most NPD cost estimation methods we found in the literature do not take the aspect of uncertainty into special consideration.

2.4.5 The challenge of data availability in NPD cost estimation

All approaches for the estimation of NPD costs rely on different kinds of data. Due to the innovative character of NPD and its influence on NPD costs in this regard, the availability of such data often represents a critical factor. In the following, we describe general guidelines for such data, where to gather it, and emphasize why this is often challenging. As described in chapter 2.3.2, we analyzed our publications regarding relevant aspects. Detailed information can be found in Table 3. Figure 11 summarizes the most relevant aspects in the context of NPD cost estimation

Guidelines	Sources	Challenges
• As much relevant data as possible • Quantitative and qualitative data • Comparability between data and projects to estimate • Maintaining/updating data • Appropriate observation period • Incorporation of experience	• Company databases • Questionnaires/ interviews/ observations • Literature/public studies	• Amount of comparable data • Adjustment of data to achieve comparability

Figure 11: Overview of guidelines, sources, and challenges in the context of data for NPD cost estimation

2.4.5.1 Guidelines for usable data in NPD cost estimation

In the following paragraphs, we summarize the six most relevant guidelines to follow for the identification of usable data for NPD cost estimation.

First, the inclusion of as much relevant data as possible is one of the key guidelines in NPD cost estimation (Roy et al. 2001) as a larger amount of raw data gives better options for cost analyses. However, this is often challenging, due to several limiting factors, which will also be subject to the remainder of this section.

Second, the data used for NPD cost estimation should not only be limited to quantitative cost data. Depending on the cost estimation technique applied, it is important to include qualitative aspects about previous projects, but also key insights regarding development processes (Roy et al. 2001). Such qualitative data might cover aspects like the composition of engineering teams in a development project. Whether they have collaborated before, could be a piece of valuable information to put previous NPD costs into perspective (Hamilton and Westney 2002).

Third, the comparability between data from previous and future projects is another guideline in NPD cost estimation (Harrold and Nicol 1977; Roy et al. 2001). Due to the varying and flexible character of development processes, only data from comparable projects should be incorporated for NPD cost estimation. Adelberger and Haft-Zboril (2015) emphasize that the most obvious way to do so is the use of data from a company's own projects. Wu et al. (2015) apply the statistical method of weighted partial least squares regression to compare the similarity of products. By doing so, they identify the most similar projects relevant for their model. Hamilton and Westney (2002) emphasize that it will usually not be possible to achieve full comparability between projects due to the variable character of NPD. Therefore, they suggest being especially aware of the differences from previous projects and adjusting the corresponding data accordingly. One of such adjustments is the aspect of ambitious estimation that might be included for future projects: Adelberger and Haft-Zboril (2015) assume a rise in efficiency. They incorporate this by applying an efficiency factor that adjusts the data of historical projects towards cost reduction in the future.

Fourth, the ongoing testing and updating of the input data for NPD cost estimation methods is an aspect repeatedly brought up as a requirement. Mousavi et al. (2015) suggest, that during the setup of the model and also afterwards it is crucial to repeatedly test and update the raw data used for the NPD cost estimation. Only by incorporating this aspect, an NPD cost estimation method can sustainably improve the cost management capabilities of a company in NPD. Gebhardt (2017) agrees that otherwise, models would falsely assume infinitely constant relationships between cost drivers and NPD costs.

Fifth, an appropriate observation period is important for the identification of usable data in NPD cost estimation. The aspects of comparability and amount of data can be contradicting in this context: Including more data from a more distant past might enlarge the database but could also lead to a loss of comparability due to changes in product development. Due to this challenging trade-off, no general statement can be made regarding the period that should be observed when looking for comparable data points. As references, Large et al. (1976) rely on data from projects between 1953 and 1970 in their study that was published in 1976. A comparable period is proposed by Bashir and Thomson (2004), who incorporate data from projects in development between 1985 and 1999 in their work from 2004.

As sixth guideline for usable data in NPD cost estimation, we find that experience plays an important role in the identification of relevant data for NPD cost estimation. Various authors emphasize the importance of experience in the context of data collection and adjustment for NPD cost estimation methods (Lambert and Sackett 1959; Steck-Winter and Šebo 2008). Holtta-Otto and Magee (2006, p.88) underline the crucial importance of experience since some databases "cannot be used effectively if the project is very different from any previous one by including radically new technology". They continue that "in these cases, the database estimation is supplemented by expert estimation". Hamilton and Westney (2002) further put focus on the aspect that experience is a valuable factor when evaluating previous cost estimation practices.

This helps evaluate and compare previous and future practices when introducing a new NPD cost estimation method to a complex system of organizational cost management practices.

2.4.5.2 Sources for usable data in NPD cost estimation

In this chapter, we emphasize the three most relevant sources of data for setting up an NPD cost estimation method: companies' cost- and product databases, data gathering methods such as questionnaires, interviews, or observations, and external data sources.

Companies' cost- and product databases are the most relevant source for setting up NPD cost estimation methods. The majority of approaches rely on historical internal cost data to establish connections between projects' characteristics and the corresponding NPD costs (Bashir et al. 2006; Bashir and Thomson 2004; Chen et al. 2020b; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). While Large et al. (1976) do so by deriving their model from cost data of 25 previous development projects of military aircraft, Hinton and Moran (1983) build on a similar approach to estimate man-hour costs for their model (Hinton and Moran 1983; Large et al. 1976). Such databases usually include information regarding projects' setups, challenges and eventually, the NPD costs occurred. Like this, a sufficient amount of data can usually be identified and incorporated in the definition of an NPD cost estimation method (Gebhardt 2017; Heller et al. 2012; Roy et al. 2001).

The generation of data, often through questionnaires or interviews can be another data source in the context of NPD cost estimation. Whether because databases are not available or because tacit qualitative data is required, additional measures must be taken in some cases. Roy et al. (2001) describe such activities, as they collect qualitative information about previous development projects through questionnaires. Other techniques to understand the specific aspects of development might be interviews or observations as done by Johnson and Kirchrain (2011) in the context of a three-month residency at an automotive company.

External information can also be a valid data source for NPD cost estimation methods. Carreyette (1977) suggests scanning for data regarding labor-hours and material costs for the development of ships in available public studies. Similar, Chen et al. (2020b) test their model by using 22 samples of general aviation aircraft development projects from the literature. In an earlier work, Chen et al. (2010) rely on relative cost differences between design alternatives for their estimation process. By doing so, they exclude the necessity of historical data. Despite these promising approaches, the incorporation of external data for NPD cost estimation is still rare in the existing body of literature.

2.4.5.3 Challenges in the context of data in NPD cost estimation

Two practical challenges regarding data availability can repeatedly be found in the literature on NPD cost estimation methods: an insufficient amount of comparable data and necessary adjustments of available raw data.

The amount of comparable data is repeatedly brought up as a major challenge in NPD cost estimation. Roy et al. (2001, p.160) give a practical explanation for this issue in their work: "There were no logbooks kept by the designers on the examined project". Despite such practical aspects, the comparability issue is often the reason for a small data sample: Various authors emphasize, that projecting information from the past can critically endanger the estimation quality due to changes in processes or external factors influencing the cost structure in NPD (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). Roy et al. (2001), as well as Salam et al. (2009), express that the variability of the design process can lead to the inability to project previous data to future product development.

Necessary adjustments of available raw data to achieve a sufficient level of comparability is another major challenge in NPD cost estimation. Scanlan et al. (2006) emphasize that in most cases, raw data must be adjusted and prepared to be used for estimation purposes. As this preparation often needs to build on vague premises and can take significant effort, this is an additional challenge to overcome. Other authors agree with this as a relevant factor by also mentioning the possible necessity to set up an information system to gather, store and adjust the input data (Heller et al. 2012; Johnson and Kirchain 2011). Experts with tacit knowledge play a significant role in doing such adjustments and are therefore brought forward as a solution to this challenge by various authors (Adelberger and Haft-Zboril 2015; Roy et al. 2001; Scanlan et al. 2006).

2.5 Conclusion

The rising importance of NPD and the corresponding cost management calls for solutions that enable organizations to estimate such costs. While overviews about cost estimation methods, in general, are already part of the literature (Altavilla et al. 2018; Niazi et al. 2006), no comprehensive summary of NPD cost estimation methods is currently available. To fill this gap, we conducted a systematic literature review. We build on a set of sources from systematic and flexible review and identify 39 publications, that deal with the challenge of NPD cost estimation.

Based on analyzing the relevant literature, we confirm the growing interest in the last two decades, especially at the intersection of engineering and management (e.g. Case 1972; Holtta-Otto and Magee 2006; Qian and Ben-Arieh 2008). The latter in combination with the dominant approach of case study research support the practical need for solutions regarding this cost-management problem (Johnson and Kirchain 2011; Love and Roper 2002; Roy et al. 2001). However, most of these studies present their methods without detailed empirical investigation of challenges that occur in an actual organizational context: They put a strong focus on the method itself, but largely neglect giving empirical evidence for the applicability of the respective method.

Our study leads to several relevant insights that enrich our understanding of NPD cost estimation. First, we show that most of the different cost estimation techniques presented by Niazi et al. (2006) are applied for the challenge of NPD cost estimation. This emphasizes the uncertain and innovative character of NPD, which denies a simple and universal solution. We identify *parametric methods*, *regression analysis models*, *activity-based costing*, *feature-based cost estimation*, and *back-propagation neural networks* as most common approaches (e.g. Bashir and Thomson 2004; Carreyette 1977; Chwastyk and Kołosowski 2014; Mousavi et al. 2015).

Second, we show that in most publications, several techniques are applied in combination to improve estimation accuracy (e.g. Li et al. 2009; Salam et al. 2009; Scanlan et al. 2006). This is consistent with the literature, where the combination of methods is proposed beneficial, especially in challenging environments for cost estimation (Altavilla et al. 2018; Niazi et al. 2006). Our findings support that this is of special importance in the area of NPD cost estimation.

As third finding, we deliver guidelines for the setup, the application, and the maintenance of NPD cost estimation methods in practice. We show that most methods follow similar steps during the setup process: An understanding of the development process must be achieved before relevant data is collected. Afterwards, relationships between that data and the corresponding NPD costs are defined. The validation of an NPD cost estimation method concludes the successful implementation of an approach (e.g. Adelberger and Haft-Zboril 2015; Hamilton and Westney 2002; Yin et al. 2015). Experts from a financial but also technical perspective are repeatedly described as a key factor for this process (e.g. Adelberger and Haft-Zboril 2015; Holtta-Otto and Magee 2006; Riedrich and Sasse 2005). We also identified the maintenance of such a method in the organizational application as a relevant activity for long-term credibility (e.g. Heller et al. 2012; Johnson and Kirchain 2011).

The fourth finding of this study is the identification of the high level of uncertainty as a major challenge for NPD cost estimation (e.g. Harrold and Nicol 1977; Mousavi et al. 2015; Zhaodong et al. 2015). However, we could observe few explicit solutions, such as monte carlo simulation, for this issue (e.g. Siddique and Repphun 2001; Zhaodong et al. 2015). This leaves room for new ideas.

The fifth finding regarding NPD cost estimation is the unveiling of the data availability problem as a critical factor. Most approaches rely on a company's internal cost database, leading to a small amount of usable information (e.g. Chen et al. 2020b; Gebhardt 2017; Large et al. 1976). The incorporation of qualitative data and expert knowledge aims to solve the data availability problem in many approaches (e.g. Roy et al. 2001; Steck-Winter and Šebo 2008). However, the amount of data, as well as the comparability between different sets of data in the dynamic world of NPD, remains a challenge for most approaches.

Like all research, this work is subject to several limitations. First, we cannot guarantee that we covered all relevant work regarding NPD cost estimation methods in NPD, as we focused our research on selected databases only. Furthermore, we did not limit our search strategy to specific quality criteria in terms of journal rankings. This approach allowed us to discover a larger variety of publications, whereas we willingly accepted a certain trade-off regarding scientific quality.

We see several promising streams for future research based on this work. First, rising cost pressure and technical disruptions call for new and innovative solutions for the NPD cost estimation problem, as the body of literature is still scarce. Second, such solutions should pay special attention to the aspects of uncertainty and the limited data availability problem. We identify these characteristics of NPD as the most critical challenges, which are not sufficiently solved in the current literature. Third, we still have limited empirical insights on organizational NPD cost estimation. By observing NPD cost estimation methods in the context of organizational applications, we would learn more about practical challenges. These insights would be helpful to further increase our knowledge. We hope that other scholars build on this work to expand the body of literature regarding NPD cost estimation, as our research shows that new and innovative solutions are needed.

3 Estimating the costs of new product development projects using external data: Introducing the NPD cost benchmarking method

Abstract

Activities for the development of new products are essential for most companies, and the investments for such activities can be substantial. Estimating these costs for new product development (hereinafter NPD) projects is a challenging process, as uncertainty is usually high and comparable data is scarce. While manifold work is available about general cost estimation methods, the estimation of NPD is still underrepresented in the literature. We contribute to this gap by introducing the *NPD cost benchmarking method*. This approach faces the data availability problem by incorporating publicly available data of competitors into a regression model to define the average product's NPD costs. In combination with a parametric model, valid NPD cost estimations can be made for early-phase product management.

Keywords: *cost estimation; new product development; R&D; method*

3.1 Introduction

The recurring introduction of innovative products to the market is crucial for most companies. Activities for this purpose are substantial for the long-term success of an organization (Brown and Eisenhardt 1995; Cooper 2019; Cui and Wu 2017; Leonard-Barton 1992; Takeuchi and Nonaka 1986). The corresponding costs can be a significant financial burden for an organization (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988). Due to the high level of uncertainty and the complex character of new product development, the management of these costs is a challenging task (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015).

Rising cost pressure and intense competition, lead to the steadily growing importance of efficient NPD cost management (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). One of the first and most important tasks in managing these costs is estimating their amount. As available resources for such projects are usually limited, a good estimate helps to avoid over- or under-spending and therefore allows efficient distribution of resources among the entire company's development portfolio (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiao-chen et al. 2009). As the development of a new product is a complex and time-consuming process, it can easily take several years until completion (Hamilton and Westney 2002; Relich 2016). This makes the estimation of the corresponding NPD costs particularly challenging, as a high level of uncertainty regarding technical solutions or market demands is the rule rather than the exception (Heller et al. 2012, 2012; Zhaodong et al. 2015).

Methods for product cost estimation are frequently discussed in the literature (e.g. Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Ruffo et al. 2006; Ruffo and Hague 2007). Several literature reviews were conducted giving systematic overviews about various product cost estimation methods (Altavilla et al. 2018; Niazi et al. 2006). Few studies focus on the unique character of NPD costs (e.g. Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003). The combination of regression analysis model and parametric methods for NPD cost estimation is proposed by several authors in this context (e.g. Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). While most of these approaches solely build on internal cost data, few include external cost information from outside the applying company as main data for their methods (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b).[10]

The current lack of methods approaching the NPD cost estimation problem calls for new solutions. While most of the few existing methods build on historical company data, the amount of data available for such approaches is often critical. Due to the innovative character of NPD, comparability to past products is difficult to obtain. Therefore, often only small data samples from within the company can be used for NPD cost estimation.

To have a new take on the data availability problem in this context, we introduce the *NPD cost benchmarking method* (hereinafter method) which incorporates publicly available data of a company's competitors to estimate the NPD costs of new products. To pursue this research, we conducted a three-year study at an international premium automotive company, in which we accompanied the development and implementation of this method as a new cost management tool for early-phase product management.

We contribute to the literature on NPD cost estimation by introducing a new method for this purpose. As many organizations struggle with estimating NPD costs in the early phase of product development, this method can function as a valuable tool in different industries. Furthermore, this work aims to raise awareness for the NPD cost estimation problem and the need for innovative solutions in fast-moving development environments.

The remainder of this chapter is structured as follows: First, we will give an overview of the existing literature on NPD cost estimation practices in NPD. After presenting the study's research design, we describe the *NPD cost benchmarking method* in detail, accompanied by a numerical example to illustrate each of its components. We conclude with a summary, limitations of this study, and an outlook on future research opportunities.

3.2 NPD cost estimation methods in the literature

The current body of literature offers a wide range of solutions for various kinds of product cost estimation problems. Such approaches range from qualitative techniques such as case-based techniques or regression analysis models to quantitative techniques such as parametric methods or activity-based costing (Niazi et al. 2006). Despite the common understanding that NPD costs play a significant role in new product development, few of these solutions explicitly handle this cost type. In this chapter, we summarize the status quo regarding NPD cost estimation in the literature and point out the gap calling for new and innovative solutions to face this challenge.[1]

The costs for activities in NPD can be a significant financial burden for an organization (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988) and about 70 to 80% of the overall life cycle cost of a product are defined during this phase (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015). Therefore, efficient management of the resources spent on these activities is crucial for a company's success. Factors, such as shorter life cycles, technological disruptions, and increasing competition, put additional cost pressure on NPD (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). To avoid inefficiencies during resource allocation among multiple parallelly developed products, an initial estimation is usually the first

[10] See chapter 2 for a comprehensive overview about NPD cost estimation methods.

measure taken in product management (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiaochen et al. 2009).

The development of new products can be an extremely challenging task, due to the lead time that can easily take several years, technical challenges, changes in market demands, and other unforeseeable factors (Hamilton and Westney 2002; Heller et al. 2012; Relich 2016; Zhaodong et al. 2015). Two aspects play an outstanding role in NPD cost estimation: the common uncertainty in NPD as well as the data availability problem. While the high level of uncertainty is a defining character trait of NPD, the data availability problem originates in the strong variety of development projects making comparability between projects challenging (Bashir et al. 2006; Bashir and Thomson 2001; Hamilton and Westney 2002; Roy et al. 2001; Salam et al. 2009; Yin et al. 2015).

Solutions for product cost estimation in the early phase of development are frequently discussed, including systematic literature reviews (Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Niazi et al. 2006; Ruffo et al. 2006; Ruffo and Hague 2007). Most of these studies focus on either overall product cost or direct material cost, but widely neglect the cost-type of NPD costs. An exception is the substream of software development, in which various methods and reviews are available. The main reason for this is the large share of development cost within such products' overall cost cases (Batra and Barua 2013; Bilgaiyan et al. 2017; Boehm et al. 1995; Rajper and Shaikh 2016). From a manufacturing industry perspective though, the existing tools for NPD cost estimation are rather limited.

An uplifting observation regarding this issue is the increasing number of methods regarding NPD cost estimation in the past two decades. Due to the difficulties described before, several different approaches were presented to solve this challenge, denying a simple superior technique for this matter. Common parts within such methods are parametric methods, often in combination with regression analysis models (Harrold and Nicol 1977; Heller et al. 2012; Scanlan et al. 2006). Other prominent techniques for NPD cost estimation are activity-based costing or feature-based cost estimation (Lambert and Sackett 1959; Liu et al. 2013; Qian and Ben-Arieh 2008). Most approaches do not rely on a single methodological approach, but rather combine aspects from different techniques (e.g. Bashir and Thomson 2001; Carreyette 1977; Li et al. 2009).

As most of these methods are based on internal data from the corresponding company, the source of information regarding project and cost details is often limited (Bashir et al. 2006; Heller et al. 2012; Relich 2016; Roy et al. 2001). This predominant focus on internal data accounts for the importance of comparability between development projects, as well as the common confidentiality regarding cost and project information. The focus on this kind of data source leaves certain limitations regarding competitive NPD cost estimation to succeed on dynamic markets. Few methods include data that is not exclusively coming from internal databases: Focusing on public cost data, the information for building NPD cost estimation methods can be expanded (Carreyette 1977; Chen et al. 2020a). We aim to contribute to this idea by introducing a method that includes NPD cost data from competitors for a new take on the data availability problem and towards a competitive NPD cost estimation model.

3.3 Research design

We had the opportunity to be involved as the *AUTO AG*, an international premium automotive original equipment manufacturer (hereinafter OEM) implemented the *NPD cost benchmarking method* as a new tool for the early-phase cost management of its development projects. During a three-year research project, the author was an active member of the company's product controlling department. In this role, he was part of a project team that implemented the method, established it as the new standard procedure in estimating new projects and further was responsible to maintain its components. This key role within the project team guaranteed access to all relevant discussions and documents in the context of the implementation and beyond, ensuring a deep understanding of the method. The researcher also made sure to keep track of all actions and development during the project period by writing a research diary as suggested by Jönsson and Lukka (Jönsson and Lukka 2006).

The approach of long-term interventionist research allowed us to gain deep and valuable insights to ensure a detailed understanding of complex structures and issues (Jönsson and Lukka 2006). Such a research approach was shown to contribute to our knowledge about phenomena in a unique way (Yin 2009). Based on this gained knowledge, we are able to deliver this method-oriented study.

3.4 The NPD cost benchmarking method

The two main components of the *NPD cost benchmarking method* are the baseline and the parametric part. Figure 12 illustrates the structure of the approach in an exemplary manner with a parametric part consisting of five cost drivers. The baseline is derived by extracting data from annual reports of relevant competitors and including them in a regression model. This baseline represents the average NPD costs for a development project in the industry. Since development projects differ in complexity, a parametric part is added. The parametric part is mostly based on internal data and experts' experience. Depending on the character of the development project, the cost drivers increase or decrease the resulting NPD cost estimation. We further introduce the concept of cost-matrices, which we apply to the baseline, as well as the cost drivers to break down the NPD cost estimation to manageable portions for the effective steering of development activities within the applying company. Thus, NPD cost estimation on industry benchmark level can be achieved, as the baseline is derived from competitors' data. The parametric part and the cost-matrices account for product- or company-specific development processes, ensuring a precise connection between project specifics and NPD cost estimation.

In the remainder of this chapter, we present the components of the method and explain how to set them up. We start with the baseline estimation, introduce the concept of cost-matrices, and then talk about the parametrization. To present the method in a tangible manner, we include an illustrative ongoing numerical example through these steps, following the method's application at the *AUTO AG*. To conclude this chapter, we present the entire model as the result of the ongoing numerical example.

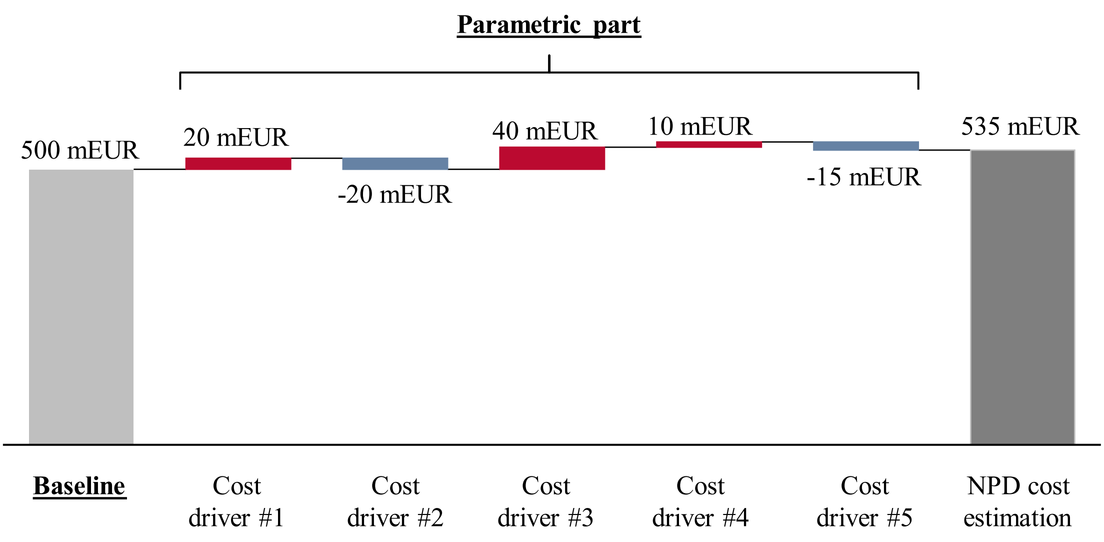

Figure 12: Illustrative overview of the *NPD cost benchmarking method* (exemplary data)

3.4.1 Baseline estimation

The baseline represents the core component of the method as it allows us to use competitors' data in NPD cost estimation. For this purpose, we use publicly available information from competitors to formulate a regression model that yields an estimation of the average NPD costs for products of each competitor. Figure 13 gives an overview of the steps towards the definition of the baseline.

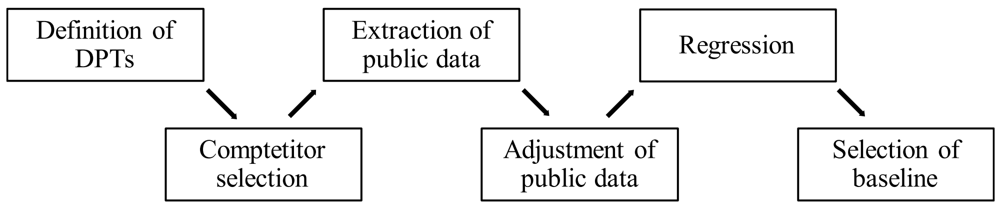

Figure 13: Steps for the baseline estimation of the *NPD cost benchmarking method*

3.4.1.1 Definition of development project types

As the baseline represents an average project, it is important to recognize that radically different development project types exist in organizational practice. Therefore, instead of having one single baseline for all projects, we generate several baselines to cluster projects to the major project types, which we call the project development types (hereinafter DPTs).

Picking the right DPTs for the application of this method is crucial and should follow several criteria: First, the DPTs must be observable in the very early phase of the development process, as that is the phase in which the method is applied for the first time. Second, the DPTs should be observable from an outside-in perspective. As we generate the baseline from competitors' data, we need to be able to cluster their projects into this scheme. The third criterion is stability through time: As we use data from several years in the past for our regression model, a classification that is independent of strategic or technological change is crucial.

For our example, we follow the *AUTO AG* during the implementation of the method and define three DPTs, as described in Table 7. They cover projects that are completely new to the company and development projects that are products derived from existing products with major or minor changes.

Table 7: Development project types (DPTs) of our numerical example

Development project type	**Description**
Development project type A (DPT A)	Completely new development projects
Development project type B (DPT B)	Development projects deviated from an existing product with major changes
Development project type C (DPT C)	Development projects deviated from an existing product with minor changes

3.4.1.2 Competitor selection

As we want the baseline to represent an external benchmark, we need to pick competitors that allow us to gain information about their spending on development costs. Several aspects have to be considered for this selection: First and most importantly, the annual spending on NPD costs needs to be publicly available, for example through annual reports. This information must be not only available for selected years, but for several consecutive years backwards starting at the most recent one available. The second requirement for the competitor selection is the comparability of reporting standards. As we will use data of the NPD spending from public information, we need to make sure that the term NPD spending has a similar definition for all the competitors selected. Even if they are following the same reporting standards, there will always be deviations in the definition of NPD spending when comparing figures from several companies. Therefore, it is later necessary to adjust the extracted data to make it sufficiently comparable to the applying company (see chapter 3.4.1.4). Third, the defined DPTs must be observable for the selected competitors during the observation period. Otherwise, it will not be possible to extract the relevant data to set up a regression model later.

From a strategic perspective, the competitor selection should be aligned with the company's main competitors. It can also make sense to include competitors that sell their products in a lower cost segment and therefore might be a good benchmark when it comes to development costs.

In Table 8 we present the two competitors we identified for our example. We assume that *AUTO AG* has one major competitor in the premium segment, namely the *Drive AG*. Furthermore, they decided to include the *Mobility SE*, which sells their vehicles in a lower price segment but has strongly gained market share from the premium segment during the last years due to the good quality they offer to the customers for a lower price than the *AUTO AG*.

Table 8: Competitors selected for our numerical example

Competitor	Description
Drive AG	The main competitor of *AUTO AG* in the premium customer segment.
Mobility SE	Offers vehicles in a lower price segment than the *AUTO AG*. Has strongly gained market share from the premium segment in the last years.

3.4.1.3 Extraction of public data

For each competitor, we need three types of information. First, need to gather the annual reports for each competitor and each year considered and extract the amount that is reported for NPD spending. Second, we need to define a *list of product launches* (hereinafter *LoPl*) for each year considered to connect the competitor's NPD spending with the corresponding products. The easiest way to gather this information would be the market research department of the applying company. If the *LoPls* of the competitors are not available within the applying company, an analysis of public statements, press releases, or access to market research databases fills the information gap. Third, we need the correct classification of the competitor's products. For the calculation of an average baseline per DPT, it is necessary to know what kind of projects the competitor developed for the NPD spending we extracted from the annual reports. Therefore, we need to apply the logic of DPTs to all products in the *LoPl* for each competitor. As this requires a certain amount of industry knowledge, experts that are familiar with the competitor's products and their technical specifications are crucial.

A key decision for the further baseline definition are the years under consideration. Several aspects are relevant for this decision: First, the years under observation should be the same for all competitors to allow a comparison. Second, the period of years selected should neither be too long nor too short. Although this seems contradictory it makes sense once we look at the procedure of the further method development. From a methodological point of view, we must consider, that the data will be used for setting up a regression model. To gain significant results from such a model, a longer observation period and therefore more data points will usually improve its quality. On the other side, we want to estimate the NPD costs for products that will be brought to the market several years in the future. This limits the period in terms of comparability since technical innovation can be expected to have an impact on a project's NPD costs.

Table 9 shows exemplary data as described for both the competitors we want to analyze during the s period from 2001 until 2019. As an example, *Drive AG* spent 1,180 mEUR in the year 2001 and launched 2 projects of DPT A, 5 projects of DPT B, and 12 of DPT C in that year.

Table 9: Raw data for the baseline estimation of our numerical example

			2001	**2002**	**2003**	**…**[a]	**2019**
Drive AG		**NPD spending**	1,180 mEUR	1,231 mEUR	1,286 mEUR	…	1,880 mEUR
	LoPl	**# DPT A**	2	1	2	…	3
		# DPT B	5	4	3		3
		# DPT C	12	9	14		8
Mobility SE		**NPD spending**	1,467 mEUR	1,417 mEUR	1,446 mEUR	…	2,059 mEUR
	LoPl	**# DPT A**	2	2	1	…	2
		# DPT B	3	3	4		4
		# DPT C	15	14	11		10

[a] We assume for both companies: $LoPl_{2003-2018} = LoPL_{2003}$.

3.4.1.4 Adjustment of public data

In the following paragraphs, we describe the steps necessary to prepare the extracted data for the use in the regression model. We distinguish between two types of activities: First, how to increase comparability of the values between the companies and through time, and second how to take care of the structural offset between the point in time that costs are reported and the time products are being launched. The steps described in the following aim to make the annual NPD spending of different companies comparable. However, the imprecise character of NPD costs can remain a threat to the credibility of the method: Since NPD activities and the respective cost structures are highly confidential in most companies, gaining full transparency is often not possible.

The most relevant adjustments to increase comparability within the data are portfolio effects, effects due to accounting law, exclusion of irrelevant cost positions, and the adjustment for inflation. Other adjustment steps may apply to specific industries and should be taken if reasonable assumptions can be made.

The first step aims to adjust the competitor's NPD costs for portfolio effects. The competitor might offer products that the applying company does not. Often, the NPD costs shown in annual reports (especially in group structures) can be distinguished between divisions of the company. NPD spending for divisions that are not comparable to the activities of the applying company should be deducted.

The next aspect to consider is a different use of accounting standards by the competitors compared to the applying company. Depending on the accounting standards applicable, companies have the choice of capitalizing parts of their NPD costs or expensing these when incurred (Lev and Daum 2004). As we want to use the actual spending on development projects, we account for different practices among the competitors.

As the next step, we must exclude irrelevant cost positions. The value for the annual costs that goes into the regression should represent the competitor’s NPD costs spent on its products. Usually, the reported NPD costs also include other cost positions, for example, basic research that is not yet assigned to a certain product. Often this distinction cannot be seen from the outside, so reasonable assumptions are necessary. It could make sense to assume that the relation between NPD costs for products and other NPD activities are roughly similar within an industry. For this reason, we suggest calculating the relation for the applying company and assuming the same factor for adjusting the competitor’s data.

While the adjustments above are implemented to make the NPD costs comparable between the companies, the adjustment for inflation is necessary to assure comparability over time. We want to set up an approach that is applicable at the current point in time, but we need to rely on data that go back several years. For this reason, we need to take this macroeconomic aspect into account and adjust the data from each year by the respective average factor of inflation.

With the regression model, we identify the average NPD costs of a vehicle product by comparing the annual NPD spending with the number of vehicles developed in that period. So far, the *LoPl* represents the products based on the time of their launch. In the next step, we adjust the *LoPl* to represent a *list of products developed* (hereinafter *LoPd*) in the respective years. We position each project to the years in which they caused NPD costs. We do this by applying the idea of cost curves, which divide the development process and the corresponding NPD costs to the years around the start of production (hereinafter SOP). As cost curves can not be observed from the outside, reasonable assumptions are needed to estimate the timely distributions of the competitors’ products.

In our example we assume that within this industry, development processes and life cycles of products are rather similar, we base this step on internal historical data of *AUTO AG*. We need to consider, that different DPTs have different cost curves. For this reason, we define and apply a separate curve for each DPT. In our example, DPT A takes longer than DPT B and DPT C as it is a completely new product and therefore needs more development time. Table 10 shows the assumed cost curves for the three DPTs in our example.

Table 10: Cost curves for our numerical example

DPT	Launch Yr. - 3	Launch Yr. - 2	Launch Yr. - 1	Launch Yr.	Launch Yr. + 1
DPT A	10%	20%	40%	20%	10%
DPT B	-	20%	45%	25%	10%
DPT C	-	15%	50%	30%	5%

Table 11 presents the adjusted data for the regression after the application of all the adjustment steps described in this chapter. We can see how these steps change the data towards increased comparability and a more appropriate match between NPD spending and the number of development projects developed during that time.

Table 11: Adjusted data for the baseline estimation of our numerical example

			2001	2002	2003	…[a,b]	2019
Drive AG		NPD spending	1,180 mEUR	1,231 mEUR	1,286 mEUR	⋯	1,880 mEUR
	Adjustments	Portfolio-effects	-100 mEUR	-110 mEUR	-95 mEUR	⋯	-150 mEUR
		Accounting standards	+50 mEUR	+40 mEUR	+10 mEUR	⋯	+70 mEUR
		Other cost positions	-75 mEUR	-76 mEUR	-77 mEUR	⋯	-86 mEUR
		Inflation	+452 mEUR	+434 mEUR	+419 mEUR	⋯	+0 mEUR
		NPD spending adj.	1,507 mEUR	1,520 mEUR	1,543 mEUR	⋯	1,714 mEUR
	LoPl	# DPT A	2	1	2	⋯	3
		# DPT B	5	4	3	⋯	3
		# DPT C	12	9	14	⋯	8
	LoPd	# DPT A	1.60[c]	1.80	1.90	⋯	2.90
		# DPT B	4.15	3.45	3.10	⋯	3.00
		# DPT C	10.80	12.40	13.75	⋯	8.30
Mobility SE		NPD spending	1,467 mEUR	1,417 mEUR	1,446 mEUR	⋯	2,059 mEUR
	Adjustments	Portfolio-effects	-80 mEUR	-90 mEUR	-75 mEUR	⋯	-110 mEUR
		Accounting standards	+20 mEUR	+35 mEUR	+15 mEUR	⋯	+30 mEUR
		Other cost positions	-94 mEUR	-89 mEUR	-89 mEUR	⋯	-94 mEUR
		Inflation	+562 mEUR	+510 mEUR	+483 mEUR	⋯	+0 mEUR
		NPD spending adj.	1,875 mEUR	1,783 mEUR	1,780 mEUR	⋯	1,885 mEUR
	LoPl	# DPT A	2	2	1	⋯	2
		# DPT B	3	3	4	⋯	4
		# DPT C	15	14	11	⋯	10
	LoPd	# DPT A	1.80	1.60	1.80	⋯	2.00
		# DPT B	3.20	3.45	3.25	⋯	3.90
		# DPT C	13.90	12.25	11.80	⋯	10.10

[a] We assume that the adjusted NPD spending for both companies is constant for the years 2003 until 2018.
[b] We assume for both companies: $LoPl_{2000} = LoPl_{2001}$ and the expected $LoPl_{2020-2022} = LoPl_{2019}$.
[c] $1.6 = 2 * 10\% + 2 * 20\% + 1 * 40\% + 2 * 20\% + 2 * 10\%$

3.4.1.5 Regression analysis model

Using a regression model, we connect the annual NPD spending of companies with the number of DPTs that they developed during that time. We derive the average NPD costs that this specific company spends on this kind of development project. We formulate a system of linear equations based on the adjusted data we prepared for each competitor C in the last section. Each equation represents the data for one year t with the adjusted annual NPD spending being the dependent variable $SPENDING_t^C$ and the number of developed DPTs of type p in that year being the independent variable $\#DPT_{pt}^C$. The parameters $COST\ DPT_p^C$ explain the effects of each independent variable on the dependent and represent the average cost per DPT in this context. The error term ε_t^C concludes the multiple linear regression model as it represents all factors influencing the dependent variable other than the parameters. Formula 2 describes the resulting model in matrix notation. Applying a regression model, with respect to its significance, will deliver values for the parameters $COST\ DPT_p^C$ which represent the average spending of competitor C for DPT p.

$$\begin{pmatrix} SPENDING_1^C \\ SPENDING_2^C \\ \vdots \\ SPENDING_t^C \end{pmatrix} = \begin{pmatrix} \#DPT_{11}^C & \#DPT_{21}^C & \cdots & \#DPT_{p1}^C \\ \#DPT_{21}^C & \#DPT_{22}^C & & \#DPT_{p2}^C \\ & \vdots & \ddots & \vdots \\ \#DPT_{1t}^C & \#DPT_{2t}^C & \cdots & \#DPT_{pt}^C \end{pmatrix} * \begin{pmatrix} COST\ DPT_1^C \\ COST\ DPT_2^C \\ \vdots \\ COST\ DPT_p^C \end{pmatrix} + \begin{pmatrix} \varepsilon_1^C \\ \varepsilon_2^C \\ \vdots \\ \varepsilon_t^C \end{pmatrix} \quad (2)$$

Formula 2: Generic multiple linear regression model for the baseline estimation (*t*: year, *p*: DPT, *C*: Company)

The amount of usable data points plays a critical role at this point. The one in ten rule is a common rule of thumb for the design of multivariate regression models (Harrell et al. 1984; Harrell et al. 1996). According to this rule, the prediction of four independent variables requires about 40 observations. In this context, estimating the baseline for four DPTs would require data from 40 years. In most cases, it will not be possible to fulfill this rule of thumb for the implementation of the *NPD cost benchmarking method*. As large companies usually develop a wide range of products, an effective NPD cost estimation tool needs to deliver reasonable outcomes for such variety. This requires the definition of several DPTs. The more DPTs, the more years need to be analyzed for more data points according to the one in ten rule. Although a larger number of years, if available, can improve a statistical relationship, relying on data from products in the distant past can be problematic for the future-oriented process of NPD. This will usually lead to a rather low number of data points for the baseline estimation. However, the significance of a regression model should still be given as a key premise for this method.

The approach of using a regression model to estimate NPD costs is not new (Bashir and Thomson 2001; Bashir and Thomson 2004; Johnson and Kirchain 2011; Zhaodong et al. 2015), but the fact of basing it on public external annual data adds a new component to NPD cost estimation, especially regarding data availability. It is important to emphasize, that this approach relies on significant correlations between the annual NPD costs extracted and adjusted and the number of observable development projects clustered by their type. If such an overall model for a competitor or one of the parameters $COST\ DPT_p^C$ does not fulfill the set significance level, this competitor's values should not be taken into consideration for the baseline definition. In such a case, several options are thinkable. On the one side, the applying company could exclude this competitor from the database for potential baselines. On the other side, they could redefine the DPTs until significance is achieved.

We continue our example and use the adjusted NPD spending per year as well as the number of DPTs according to the *LoPd* as input. Table 12, Formula 3, and Table 13 show the input data, the equation system for the regression, and its results for the *Drive AG*. For the detailed data on the *Mobility SE*, please be referred to Appendix B.

Table 12: Input data for the regression analysis model for the baseline estimation of our numerical example (*Drive AG*)

		List of projects developed		
Year *t*	$\#DPT_{At}^{Drive\ AG}$	$\#DPT_{Bt}^{Drive\ AG}$	$\#DPT_{Ct}^{Drive\ AG}$	$SPENDING_{t}^{Drive\ AG}$
2001	1.6	4.15	10.8	1,507 mEUR
2002	1.8	3.45	12.4	1,520 mEUR
2003	1.9	3.1	13.75	1,543 mEUR
2004	2	3.00	14	1,543 mEUR
2005	2	3.00	14	1,543 mEUR
2006	2	3.00	14	1,543 mEUR
2007	2	3.00	14	1,543 mEUR
2008	2	3.00	14	1,543 mEUR
2009	2	3.00	14	1,543 mEUR
2010	2	3.00	14	1,543 mEUR
2011	2	3.00	14	1,543 mEUR
2012	2	3.00	14	1,543 mEUR
2013	2	3.00	14	1,543 mEUR
2014	2	3.00	14	1,543 mEUR
2015	2	3.00	14	1,543 mEUR
2016	2.1	3.00	14	1,543 mEUR
2017	2.3	3.00	13.1	1,543 mEUR
2018	2.7	3.00	10.1	1,543 mEUR
2019	2.9	3.00	8.3	1,714 mEUR

$$\begin{pmatrix} 1{,}507 \\ 1{,}520 \\ 1{,}543 \\ \vdots \\ 1{,}714 \end{pmatrix} = \begin{pmatrix} 1.60 & 4.15 & 10.80 \\ 1.80 & 3.45 & 12.40 \\ 1.90 & 3.10 & 13.75 \\ & \vdots & \\ 2.90 & 3.00 & 8.30 \end{pmatrix} * \begin{pmatrix} COST\ DPT_{DPT\ A}^{DRIVE\ AG} \\ COST\ DPT_{DPT\ B}^{DRIVE\ AG} \\ COST\ DPT_{DPT\ C}^{DRIVE\ AG} \end{pmatrix} \tag{3}$$

Formula 3: Regression model for baseline estimation in numerical example (*Drive AG*)

Table 13: Result of the linear regression analysis of our numerical example (*Drive AG*)

	Linear regression model for baseline (*Drive AG*)		
	Unstandardized coefficients		
	B	St. error	t
$COST\ DPT_{DPT\ A}^{DRIVE\ AG}$	297.709***	20.120	14.797
$COST\ DPT_{DPT\ B}^{DRIVE\ AG}$	173.979***	18.086	9.620
$COST\ DPT_{DPT\ C}^{DRIVE\ AG}$	29.999***	3.517	8.531
R^2		1.00	
R^2 adjusted		1.00	
F		12858.948***	
n		19	

*p < 0.10; ** p < 0.05; *** p < 0.01

The exemplary regression model for the *Drive AG* delivers significant results for the overall model as well as for the three independent variables $COST\ DPT_p^C$ representing the average NPD costs per DPT. Based on the model, we learn that the competitors' NPD spending can be explained through the number of their DPTs. The coefficient values represent the NPD costs for a single development project of the corresponding type. We can estimate that *Drive AG* spends about 298 mEUR on an average DPT A, 174 mEUR on an average DPT B, and 30 mEUR on an average DPT C. Table 14 summarizes the results per DPT for *Drive AG* as well as *Mobility SE,* compared to the actual average NPD costs per DPT of the *AUTO AG*.

Table 14: Results of the regression analysis models for *Drive AG* and *Mobility SE* compared to the actual average NPD spending of the *AUTO AG*

	$\boldsymbol{C = Drive\ AG}$	$\boldsymbol{C = Mobility\ SE}$	$\boldsymbol{C = AUTO\ AG}$[a]
$\boldsymbol{COST\ DPT_{DPT\ A}^C}$	298 mEUR	243 mEUR	350 mEUR
$\boldsymbol{COST\ DPT_{DPT\ B}^C}$	174 mEUR	199 mEUR	210 mEUR
$\boldsymbol{COST\ DPT_{DPT\ C}^C}$	30 mEUR	58 mEUR	65 mEUR

[a] average costs for development projects of *AUTO AG* in the past

3.4.1.6 Selection of baseline

The outcomes of the regression models, which represent estimated average NPD costs of competitors, give us a range of options for the selection of baselines. One way would be to aim for a best-in-class approach, selecting the lowest value for each DPT. From a targeting perspective, this would be the most radical choice regarding the cost ambition of the applying company. Another method for the selection of the baselines would be a single-competitor approach, meaning to set the baseline on the values of a specific competitor. This might make sense in cases where one major competitor exists which functions as a role model regarding NPD cost-efficiency through the entire product portfolio. In some cases, companies might also tend to deviate from a systematic approach and pick the baselines for each DPT individually, leading to a rather subjective selection. This decision marks a crucial point of the method, and we recommend considering two major aspects for picking the baselines: the company's portfolio strategy and its financial situation.

A different portfolio strategy might be the reason for deviations between the competitors' outcomes of the regression analysis. A portfolio strategy that builds on a varying composition of DPTs might lead to higher spending for a certain DPT while the NPD costs for another DPT are significantly lower. A good example would be different platform strategies in the automotive strategy. If the applying company desires to move closer to a competitor's portfolio strategy, picking such competitors for the baseline can be a valid path.

The financial situation of the applying company should also play a significant role: If the organization acts under a high level of cost pressure, the selection of lower baselines can help give arguments for reducing the overall NPD costs. A realistic evaluation of the feasibility for the applying company should be done in any case. This might be done with the help of experts and an analysis of previous projects' NPD costs.

Table 15 shows the baseline that we select for our example after considering the points described in this section. The *AUTO AG* goes for a best-in-class approach for DPT A and DPT B. For DPT C they decided that the lowest value (*Drive AG*) cannot be used as the historical NPD costs for this type of project by the *AUTO AG* was more than twice that value. Therefore, we pick the value of *Mobility SE* as a feasible baseline for DPT C.

Table 15: Baselines selected for each DPT in our numerical example

	$C = Drive\ AG$	$C = Mobility\ SE$	$C = AUTO\ AG$[a]
$COST\ DPT^{C}_{DPT\ A}$	298 mEUR	**243 mEUR**	350 mEUR
$COST\ DPT^{C}_{DPT\ B}$	**174 mEUR**	199 mEUR	210 mEUR
$COST\ DPT^{C}_{DPT\ C}$	30 mEUR	**58 mEUR**	65 mEUR

[a] average costs for development projects of *AUTO AG* in the past

3.4.2 Definition of cost-matrices

With the cost-matrices as a component of the *NPD cost benchmarking method*, NPD costs are broken down into various processes, departments, or components to enable the efficient management of development activities within a company. The cost-matrices are applied to the baseline as well as to the cost drivers. We set up a specific matrix for each baseline and each combination of DPT and cost driver.[11] This accounts for the fact, that the split of NPD costs significantly varies per DPT as well as per cost driver.

The cost-matrices must fit the company's cost management process and can usually be represented by a two-dimensional matrix. A development project consists of several major technical components that must be controlled individually. These technical components represent one dimension of the matrix. For the second dimension, we consider the several departments involved in developing technical components. These departments are usually also managed through a budgeting process. Therefore, the second dimension represents the development departments.

Table 16 shows an exemplary structure of the cost-matrices. The intersection of development project component $DPC\ n$ and development department $DD\ z$ is the NPD cost percentage $C\%^{z}_{n}$ that is assigned to the development activities in the department $DD\ z$ for the component $DPC\ n$ for a particular cost object. Such a matrix is set up for each baseline as well as for every combination of DPT and cost driver so specific cost structures are respected.

[11] More on the cost drivers in the parametric part of this method in chapter 3.4.3.

Table 16: Generic illustration of the concept of cost-matrices

	$\boldsymbol{DD\ A}$	$\boldsymbol{DD\ B}$	…	$\boldsymbol{DD\ z}$
$\boldsymbol{DPC\ 1}$	$C\%_1^A$	$C\%_1^B$	…	$C\%_1^z$
$\boldsymbol{DPC\ 2}$	$C\%_2^A$	$C\%_2^B$	…	…
…	…	…	…	…
$\boldsymbol{DPC\ n}$	$C\%_n^A$	$C\%_n^B$		$C\%_n^z$

Defining the cost-matrices can be a challenging task, as it requires significant effort and data, either based on historical information or experts' experience. The process usually follows an iterative approach going back and forth. The data required can come from different sources depending on the applying company. Often, a detailed analysis of previous projects will help get an overview, but in most cases, that information cannot be transferred to the cost-matrices without adjustments by experts. Such adjustments can be necessary for various reasons. Development processes might have changed drastically which makes comparisons to their cost structure invalid. Furthermore, the projects in the past might not represent an ideal distribution that the company desires. Although such discussions cause significant effort, leading them to agreed premises is crucial for the method's later credibility.

The aspect of modular components plays an important role in the context of this method. Many companies rely on modular product architectures to achieve higher cost-efficiency. However, this bears certain challenges for the application of this method. The NPD costs for the development of such modular structures are usually shared among all products using them. The other way around, a product will use modular components from other products and must pay compensation for them. As the outcome of this method represents the entire NPD costs of a product, we can assume that the compensations for modular components are included in the method's outcome. By breaking the NPD costs down to its modular components through cost-matrices though, we assume a value that represents the NPD costs that the product can afford for modular components. As these compensations depend on the NPD costs of several other development projects, complexity and dependencies critically endanger the interpretability of these values. A solution could be the application of the method for each development project within the company or group to define the overall NPD costs of the development portfolio. In the next step, the compensations between the projects would have to be defined to calculate the required resources for each project. This solution might be challenging to perform in practice though, due to the intense complexity of and interactions between NPD activities in organizations.

We also set up cost-matrices for the *AUTO AG*, which manages its products from a technical perspective in two main parts: the *chassis* and the *body*. Furthermore, *AUTO AG* has two major development departments: the *department for mechanical engineering* (hereinafter *ME*) and the *department for electrical engineering* (hereinafter *EE*). This leads to the matrices for the three DPTs as shown in Table 17. We can see that the *AUTO AG* pursues the strategy to focus their development activities on the chassis and especially mechanical parts in completely new products (DPT A). The fewer new parts a project must develop, the more they focus the NPD spending on the body and electrical components. For simplicity reasons, we assume that the cost split is equal for each DPT-Baseline and each cost driver per DPT.

Table 17: Cost-matrices for DPT A, DPT B, and DPT C for our numerical example

	DPT A		DPT B		DPT C	
	ME	**EE**	**ME**	**EE**	**ME**	**EE**
Chassis	40%	35%	25%	25%	10%	20%
Body	15%	10%	25%	25%	30%	40%

3.4.3 Parametrization

The definition of the DPTs already accounts for a certain variety in the development projects' resource requirements. However, we aim for a more precise estimation of NPD costs, as development projects strongly vary in their complexity (Joglekar and Ford 2005; Loch and Kavadias). We achieve that by implementing a parametric model to complement the baseline. We identify significant cost drivers that increase or decrease the overall NPD costs of the development project. This increase or decrease is always formulated in relation to the baseline, which represents an average development project with average NPD costs. For each cost driver, we set possible levels and estimate their quantified effect on the NPD costs. These steps must be taken for each DPT individually, as they will most likely differ. Figure 14 shows the parametric part in the context of the entire method. In the remainder of this section, we describe the three steps of cost driver identification, identification of their levels, and their quantification.

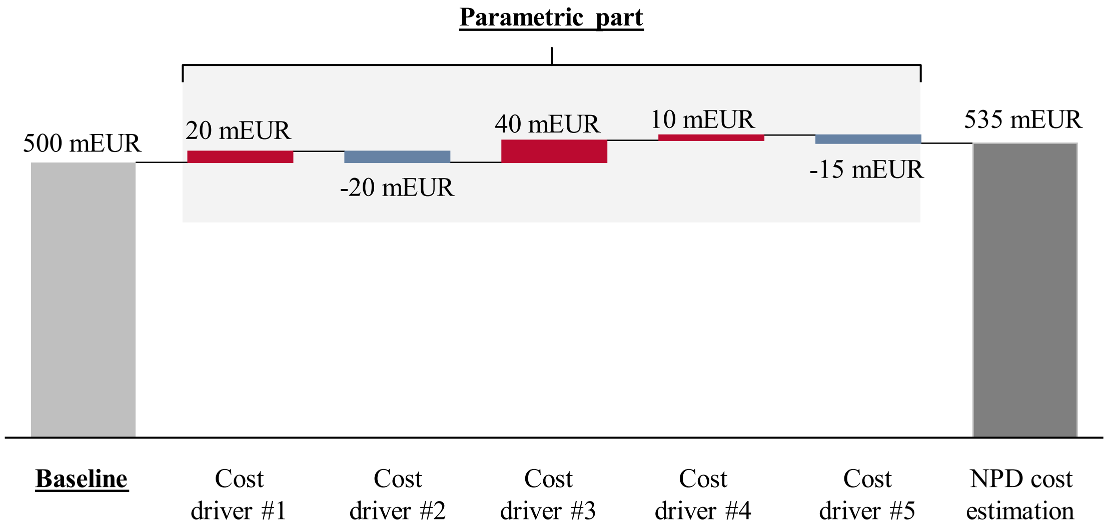

Figure 14: Illustrative overview of the *NPD cost benchmarking method* (focus on parametric part) (exemplary data)

3.4.3.1 Identification of the cost drivers

Several aspects must be considered during the identification of relevant cost drivers. First, we need to make sure, that the cost drivers are observable. As we want to use this method in the early phase of product development, we need to make sure that the information we need to apply this method, is already available.

Second, we must ensure a reasonable complexity of cost drivers. In practice, it will neither be possible nor desired to consider all cost drivers for the NPD costs of a development project. Therefore, the identified cost drivers should represent the most important factors in the sense of the Pareto principle.

Third, we should make sure to avoid overlaps between cost drivers. Later, we will quantify the possible levels of each cost driver by their effects on the NPD costs. If there is an overlap between cost drivers in terms of content, this can lead to the over-representation of certain factors.

The fourth aspect we want to point out during the cost driver identification is the applicability to the DPTs. Not all cost drivers have to be relevant for each DPT. Some of them are likely to be specific to certain project types while some of them have a rather general character.

Table 18 continues our example. Within the development processes of *AUTO AG*, we identified three relevant cost drivers: the customer segment, the body type, and the number of different wheelbases. While Cost Drivers #1 and #2 apply to all DPTs, Cost Driver #3 is only relevant for DPT A because the number of different wheelbases is only relevant for completely new projects. Deviated projects should use existing components and are therefore limited regarding this cost driver.[12]

Table 18: Cost drivers for the parametric part of our numerical example

		relevant for		
Cost driver	**Description**	**DPT A**	**DPT B**	**DPT C**
Cost driver #1	Customer segment	x	x	x
Cost driver #2	Body type	x	x	x
Cost driver #3	Number of different wheelbases	x	-	-

3.4.3.2 Identification of levels per cost driver

We want to identify, which levels the defined cost drivers can have. For this task, we follow the three steps of level identification, relevance-check, and baseline level definition.

First, we need to identify for each cost driver individually, which levels are possible in a development project. In some cases, these will be numbers and the distinction between levels is clear.[13] In cases in which the levels are not quantities, but qualitative project characteristics, their distinction can be challenging. In both cases, it makes sense to define the levels in a way that the complexity of the model remains manageable. We further want to emphasize, that the method also functions as a steering tool. In that sense, it can make perfect sense to limit the possible levels for certain cost drivers if we do not want certain things to be an option during product definition.[14]

The next step is to define the relevant levels for each cost driver and each DPT. Here, the steering mechanism becomes more important. The applying company must define the options that they want to allow for different project types. It might make sense to have the full range of levels available for DPT A

[12] We reduce the model to three cost drivers for better readability. In practice, more than three cost drivers will be necessary.

[13] E.g. for cost driver #3 in our example.

[14] E.g. for dost driver #3 in our example, the highest level could be three different wheelbases as we want to reduce complexity within the products to avoid overspending in the future.

in our example, while DPT C represents a project with just minor deviations from previous products and therefore should have fewer or even no options.[15]

For the last step, we go back to the definition of the baseline. As each baseline represents an average project, we must define which level per cost driver the baseline level is. This will define whether a selected level of a cost driver increases or decreases the overall NPD costs and therefore sets the reference point for the quantification of cost driver effects. As the baseline is set up from development projects of competitors, the baseline level should be the average level of the competitor that was selected for the respective baseline. As some of the defined cost drivers might be very specific for the applying company or simply not observable for the competitor, reasonable assumptions must be made.

We conclude this section with the application of the steps described in the example of *AUTO AG*. Table 19 gives an overview of the relevant levels for each cost driver and each DPT, as well as the corresponding baseline levels. We see that while the baseline level for the customer segment is the B segment for DPT A and DPT B, the average competitors' DPT C represents a C segment vehicle. Furthermore, *AUTO AG* decided, that products of DPT C should not be developed as a cabriolet, as this expensive body type should not be planned for products with minor changes.

Table 19: Relevant levels and baseline levels per cost driver and DPT in numerical example

				relevant for	
Cost driver	**Description**	**Possible levels**	**DPT A**	**DPT B**	**DPT C**
Cost driver #1	Customer segment	A segment	x	x	x
		B segment	x (baseline)[a]	x (baseline)	x
		C segment	x	x	x (baseline)
		D segment	x	x	x
Cost driver #2	Body type	Sedan	x (baseline)	x	x
		Hatchback	x	x (baseline)	x (baseline)
		Coupé	x	x	x
		SUV/CUV	x	x	x
		Cabriolet	x	x	not relevant
Cost driver #3	Number of different wheelbases	1 wheelbase	x	not relevant	not relevant
		2 wheelbases	x (baseline)		
		3 wheelbases	x		

[a] The baseline level resembles the average level in the baseline. If this level is selected, the baseline is neither increased nor decreased.

3.4.3.3 Quantification of levels per cost driver and DPT

To finalize the parametric part of the method, we need to quantify the increases or decreases of each cost driver level for each DPT compared to the baseline. This is one of the most complex parts of implementing this method at a company. The cost databases of most companies will not have the level of detail to identify actual cost differences for each cost driver level, because interdependencies within a product's development make it challenging to determine their effects separately. However, available historical values can be a valuable starting point and should be included in this step. More important though, is the involvement of experts familiar with the cost effects due to changes within product architecture or development processes. Cross-functional discussions will help to define values that are considered valid but also to gain

[15] E.g. for cost driver #2 in our example, DPT A might be of any body type, while DPT C should not be allowed to be developed as (expensive) cabriolet.

credibility towards relevant stakeholders. As the baseline comes from external data, it would only make sense, to include data from competitors for the quantification as well. However, due to the confidential and process-specific character of NPD, this is not an option in most cases.

Table 20 concludes our example showing the increase or decrease per cost driver and DPT. For simplicity reasons, we assume that each cost driver for a DPT has the same cost-matrix.[16] As an example, a C segment hatchback of DPT A with one wheelbase would increase the estimation coming from the baseline by 20 mEUR.[17]

Table 20: Quantified levels per cost driver and DPT in our numerical example (in mEUR)

Cost driver	Description	Possible levels	DPT A	DPT B	DPT C
Cost driver #1	Customer segment	A segment	-30	-20	-10
		B segment	+/- 0	+/- 0	-5
		C segment	+20	+15	+/- 0
		D segment	+40	+30	+10
Cost driver #2	Body type	Sedan	+/- 0	-7	-5
		Hatchback	+10	+/- 0	+/- 0
		Coupé	+15	+10	+5
		SUV/CUV	+30	+20	+10
		Cabriolet	+50	+30	not relevant
Cost driver #3	Number of different wheelbases	1 wheelbase	-10	not relevant	not relevant
		2 wheelbases	+/- 0		
		3 wheelbases	+10		

3.4.4 Results of the numerical example

In the previous sections, we defined the elements of the *NPD cost benchmarking method*. We explained, how the baseline represents an external benchmark as it is deviated from competitors' publicly available data. We further talked about the concept of cost-matrices and their application to the baseline of each DPT as well as for each combination of DPT and cost driver. In the last step, we made sure that the NPD cost estimation derived with this method is adjusted to project- and company-specific cost requirements by defining the cost drivers and their effects on the baseline. Before we present the results of our numerical example with the help of several exemplary projects, we want to point out two relevant aspects for any practical application: the method's validation and its maintenance.

Before applying the method to actual development projects, we recommend validating the outcome of the method. This will help making sure that it delivers valid results in various kinds of analyses and application scenarios. The easiest way to do this is to compare the actual NPD costs of development projects to the method's estimation for these projects. Based on the results of such validation, components of the method can be re-evaluated and adjusted until a sufficient status is achieved.

A maintenance process will help to keep the components up to date. This is necessary, as technical challenges, their solutions, or the development process, in general, will most likely change over time. While we recommend updating the baseline every few years, the other components should be subject to a more

[16] See 3.4.2 for the defined matrices.

[17] 20 mEUR = 20 mEUR + 10 mEUR – 10 mEUR

continuous maintenance process. For this purpose, an expert team that regularly considers possible adjustments should be installed.

To conclude *AUTO AG's* example, we apply the method to several exemplary projects. We build on the baselines, the cost-matrices, and the cost drivers defined in Table 15, Table 17, and Table 20. In Table 21 we apply the method to five exemplary projects. The resulting NPD cost estimations show, how the parametric part accounts for project-specific complexity in terms of NPD cost requirements. Like this, the first three projects are estimated between 203 mEUR and 343 mEUR, despite being the same DPT. We also see the effect of the cost-matrices in breaking the NPD cost estimation down to the components and departments: While the NPD cost estimation for the body of the first project would be 66 mEUR, the body of the second project is estimated with 86 mEUR due to its higher technical complexity.

Table 21: Results of the numerical example of the *NPD cost benchmarking method* applied to five exemplary projects

	Delta compared to baseline							
Exemplary projects	***Baseline***	*Customer segment*	*Body type*	*No. of wheelbases*	**NPD cost estimation**			
1. The brand-new generation of the most sold model of the *AUTO AG*. As always, customers in the C segment are the target group for this sedan. No specific technical complexity is required.						*ME*	*EE*	
	DPT A	C segment	Sedan	2 wheelbases	*Body*	39 mEUR	26 mEUR	66 mEUR
	243 mEUR	+20 mEUR	+0 mEUR	+0 mEUR	*Chassis*	105 mEUR	92 mEUR	197 mEUR
						145[a] mEUR	118 mEUR	**263 mEUR**
2. Since the main competitor is working on a premium cabriolet in the highest price segment, *AUTO AG* wants to follow. To attract customers in North America as well as in China, a larger variety of wheelbases is necessary.						*ME*	*EE*	
	DPT A	D segment	Cabriolet	3 wheelbases	*Body*	51 mEUR	34 mEUR	86 mEUR
	243 mEUR	+40 mEUR	+50 mEUR	+10 mEUR	*Chassis*	137 mEUR	120 mEUR	257 mEUR
						189 mEUR	154 mEUR	**343 mEUR**
3. This new model will be the "next big thing" in terms of urban mobility. This sedan is designed for young customers that require a compact car for a reasonable price. To reduce NPD costs, it will only be available with a single wheelbase.						*ME*	*EE*	
	DPT A	A segment	Sedan	1 wheelbase	*Body*	30 mEUR	20 mEUR	51 mEUR
	243 mEUR	-30 mEUR	+0 mEUR	-10 mEUR	*Chassis*	81 mEUR	71 mEUR	152 mEUR
						112 mEUR	91 mEUR	**203 mEUR**
4. Project 3 was a big success. The company decides to develop a similar model, but as a Sport Utility Vehicle. Some designers argued for a change in the wheelbase, but since the method showed that being too expensive for such a DPT, they decided against a change.						*ME*	*EE*	
	DPT B	A segment	SUV/CUV	not relevant	*Body*	44 mEUR	44 mEUR	87 mEUR
	174 mEUR	-20 mEUR	+20 mEUR	-	*Chassis*	44 mEUR	44 mEUR	87 mEUR
						87 mEUR	87 mEUR	**174 mEUR**
5. As always, a hatchback version of project 1 is developed for customers requiring a sportier look. Since this model still can use many carry-over parts from the sedan, only minor changes are necessary.						*ME*	*EE*	
	DPT C	C segment	Hatchb.	not relevant	*Body*	17 mEUR	23 mEUR	41 mEUR
	58 mEUR	+0 mEUR	+0 mEUR	-	*Chassis*	6 mEUR	12 mEUR	17 mEUR
						23 mEUR	35 mEUR	**58 mEUR**

[a] Inaccuracies in sums are the consequence of mathematical rounding.

3.5 Conclusion

In this chapter, we present the *NPD cost benchmarking method*, which incorporates publicly available data of a company's competitors to estimate the NPD costs of new products. With rising cost pressure and intense competition, the importance of efficient NPD cost management is steadily growing (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). However, few scholars present methodological approaches to estimate NPD costs (e.g. Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003). Common issues in NPD cost estimation are the high level of uncertainty and the small amount of available data due to the innovative character of NPD (Bashir et al. 2006; Bashir and Thomson 2001; Harrold and Nicol 1977; Mousavi et al. 2015; Roy et al. 2001; Salam et al. 2009; Yin et al. 2015; Zhaodong et al. 2015).

The *NPD cost benchmarking method* represents a regression analysis model in combination with a parametric method. Such a methodological approach is common for NPD cost estimation methods (e.g. Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). While a regression model establishes a relationship between historical data and specific characteristics or variables of the corresponding cost object, a parametric model allows to express such relationships with tangible cost drivers (Niazi et al. 2006). Like this, the method seamlessly fits into the existing body of literature.[18]

Building this method on external data from annual reports is a novel take on the data availability problem in NPD cost estimation. Most existing methods for NPD cost estimation are based on historical cost data from within the applying company (e.g. Chen et al. 2020b; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). While our method also includes historical internal data, especially in its parametric part, the baseline takes an outside-in perspective on competitors' data. Using such publicly available data for NPD cost estimation is not entirely new, but existing approaches either use public cost data on specific development projects or development processes (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). Instead of using such limited and fragmented public data samples, the *NPD cost benchmarking method* takes a detour through the annual reports of relevant competitors to reconstruct the average NPD costs per project. This enables it to estimate competitive NPD costs on a product level in industries where such data is not available. By solving the data availability problem in this manner, the method opens a new path for NPD cost estimation techniques.

The parametric part of this method which is mostly based on internal data and experts' experience is incorporated to account for company-specific development processes as well as the bandwidth in product complexity. The parameters are designed to be observable in the early product phase already and identified and applied with the help of experienced experts. Like this, the systematic high level of uncertainty in NPD is not problematic for the application of this method. While few other methods include techniques such as monte carlo simulation or fuzzy numbers to particularly account for uncertainty, the *NPD cost benchmarking method* does not include such a mathematical approach (Siddique and Repphun 2001; Zhaodong et al. 2015). Relying on experienced experts to face the high level of uncertainty in NPD is a common approach, which aligns this method with other approaches previously presented (e.g. Hinton and Moran 1983; Lambert and Sackett 1959).

This work is subject to several limitations. First, we cannot fully exclude a potential bias. Due to the researcher's active part in the case company's daily doing, there is always a risk to focus only on insights in favor of an initial idea due to personal involvement (Norris 1997). Second, we observed the method during a limited period. For further insights on its credibility in the actual organizational application, we

[18] See chapter 2 for a comprehensive overview about NPD cost estimation methods.

suggest analyzing the *NPD cost benchmarking method* in a longer and more qualitative practice-oriented investigation.[19]

We propose two promising research opportunities based on this work. First, we see possibilities to improve how the method incorporated the factor of uncertainty in NPD. An extension based on mathematical approaches as shown by scholars (e.g. Siddique and Repphun 2001; Zhaodong et al. 2015) might be worthwhile. Second, we motivate scholars to investigate the NPD cost estimation problem for modular components. Due to the complex interconnection of such development projects throughout a product portfolio, NPD cost management for modular components is challenging (Marion and Meyer 2018; Skirde et al. 2016; Stadtherr and Wouters 2021). We identify this as a potential weak point of this method and support the development of ideas for further improvement. We hope that other scholars feel motivated and inspired to reach for new solutions regarding the rising challenge of cost estimation in the fast-moving environment of NPD.

[19] See chapter 4 for a case study on the *NPD cost benchmarking method* in practice.

4 The NPD cost benchmarking method in practice: a case study

Abstract

The estimation of costs in the uncertain and complex environment of new product development (hereinafter NPD) is challenging. Although several authors present methods for this task, little detailed insights are given about challenges that occur in the environment of NPD cost estimation in actual organizations. We contribute to this gap through a three-year case study, in which we were present as the *AUTO AG* implemented the *NPD cost benchmarking method* (hereinafter method). Along the dimensions of credibility and data, we investigate several research questions to improve our understanding of challenges in NPD cost estimation in general and the *NPD cost benchmarking method* in particular. We show that active change management can improve the credibility of a new NPD cost estimation method applied at a company. We point out that the combination of regression analysis models and parametric methods is particularly well suited for this estimation environment, due to its highly appropriate level of explainability. We show how the *NPD cost benchmarking method* is an ideal tool for long-term estimation scenarios and especially portfolio management, while it suffers credibility when applied in the short term. Similar, we do not recommend its application for the estimation of modular structures. Regarding the dimension of data in NPD cost estimation, we unveil the comparability problem as the main challenge for approaches building on external data. We also show that the regularly poor data quality in this environment is not as problematic in practice as expected, also because it can often sufficiently be replaced by expert knowledge.

Keywords: *new product development; cost estimation method; R&D; case study*

4.1 Introduction

Product development activities are crucial for most companies that depend on repeatedly bringing innovative products to the market (Artz et al. 2010; Brown and Eisenhardt 1995; Chao and Kavadias 2008; Hauser et al. 2006; Talay et al. 2014). The corresponding costs can be a significant financial burden for an organization (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988). Due to the long, uncertain, and complex character of product development, managing these costs is a challenging task (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015). At the same time, the importance of efficient NPD cost management is constantly growing due to rising cost pressure and intense competition (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). Estimating a project's NPD costs is one of the first and most important tasks in this context: As available resources for such projects are usually limited, a good estimation avoids over- or under-spending and therefore allows efficient distribution of resources among the entire company's development portfolio (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiao-chen et al. 2009). Due to a high level of uncertainty regarding aspects such as technical solutions or market demands, coming up with a reliable NPD cost estimation is often challenging (Heller et al. 2012, 2012; Zhaodong et al. 2015).

Methods for project cost estimation in general and especially for the early product phase are frequently discussed in the literature (e.g. Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Niazi et al. 2006; Ruffo et al. 2006; Ruffo and Hague 2007). The unique character of NPD costs though is subject to few studies (e.g. Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959;

Tu and Xie 2003).[20] Most of these existing studies present empirical aspects, especially in the form of case study research. However, the focus of these works mostly lies in the presentation of NPD cost estimation methods based on practical examples. Like this, they aim to deliver solutions to the NPD cost estimation problem. What they do not deliver, are detailed insights on challenges that arise in actual organizations when attempting to estimate NPD costs. Such insights would go beyond the presentation of NPD cost estimation methods and help sharpen our understanding of the challenging process of NPD cost estimation.

In this study, we empirically investigate challenges in NPD cost estimation from the two dimensions credibility and data. We do so by conducting a case study at the *AUTO AG*, an international premium automotive company, which we accompanied during the implementation and application of the *NPD cost benchmarking method*. Our research questions and the corresponding findings focus partly more general on challenges in NPD cost estimation and partly on that specific method. During the three-year research project, we were actively involved in the development, implementation, and application of the *NPD cost benchmarking method*. This NPD cost estimation method builds on external publicly available data of a company's competitors to estimate the NPD cost of new products.[21] We build our analyses on the analysis of relevant documents and emails, observations caught in a research diary, as well as a series of discussion-style interviews.

The first dimension we contribute to with this study is the aspect of credibility in NPD cost estimation in general as well as the *NPD cost benchmarking method* in particular. The importance of credibility in the context of cost estimation was emphasized by previous scholars (Prince 2002; Smith and Mason 1997) but has not been subject to existing studies on NPD cost estimation.

As first contribution to the aspect of credibility in NPD cost estimation, we find that active change management, as promoted by other scholars in a more general context (Burnes and Jackson 2011; By 2005; Gill 2002), can effectively improve the credibility of a newly implemented NPD cost estimation method. Through active communication, considerate adjustment to a company's requirements, and regular activities for keeping the method up to date, its credibility in the organizational application can be increased.

The second contribution lies in the emphasis on the methodological combination of regression and parametric models as highly credible for NPD cost estimation. We empirically confirm this concept which is present in the literature on NPD cost estimation methods, but so far without detailed empirical insights (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009).

Our third and fourth contributions in the context of credibility in NPD cost estimation are related to the first detailed empirical investigation of the *NPD cost benchmarking method* and its challenges in an actual organization. As a third contribution, we uncover the application with a focus on the long-term NPD cost management of an entire development portfolio as the most credible application scenario of the method. We do not recommend the short-term application. Therefore, we see the method as an ideal addition to the toolset in the context of strategic planning activities (Fairholm and Card 2009; Feurer and Chaharbaghi 1995; Peter and Jarratt 2015). As a fourth contribution, we empirically unveil that the estimation of modular components is a major weak point of the method. The development of modular structures has shown to be of relevance for many industries (ElMaraghy et al. 2013; Jose and Tollenaere 2005; Ramdas et al. 2003), and the cost management in this context is especially challenging (Marion and Meyer 2018; Skirde et al. 2016; Stadtherr and Wouters 2021). Based on our empirical insights, we do not recommend solely building on the *NPD cost benchmarking method* for this estimation purpose.

The second dimension of data plays a central role in NPD cost estimation, as all approaches for this purpose build on some kind of data. However, this data is often scarce (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015) and existing approaches mostly build on internal NPD cost

[20] See chapter 2 for a comprehensive overview about NPD cost estimation methods.

[21] See chapter 3 for more information about the *NPD cost benchmarking method*.

data only (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976).

The fifth contribution of this study lies in the unveiling of the comparability problem as the main challenge for the use of external data in NPD cost estimation. While the majority of methods for NPD cost estimation builds on internal data from an organization's previous products (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976), few scholars also incorporate external data in their approaches (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). Our observations show that the *NPD cost benchmarking method*, as one example of an approach building on external data, can be functional for NPD cost estimation purposes. However, we could also see the main challenge of such approaches: the comparability between internal and external NPD costs. NPD cost estimation methods based on external cost data must include solutions or adjustment steps to react to the comparability problem, similar to general guidelines for inter-company benchmarking activities (Bhutta and Huq 1999; Markin 1992; Shetty 1993). However, even with such activities, full comparability will most likely never be achievable due to the highly company-specific aspects of NPD.

The sixth and seventh contributions of this study consider the way companies deal with data of poor quality in NPD cost estimation, which is often named as a major challenge in NPD cost estimation (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). As a sixth contribution, we find that the problem of poor-quality data in NPD cost estimation is not as critical as expected. Stakeholders in organizations that are familiar with the topic of NPD cost estimation are aware of this challenge and lower their expectations towards the amount of usable data in this regard. As seventh contribution, we find that expert knowledge can sufficiently replace data of poor quality for NPD cost estimation. The extraction of such tangible information is crucial in the context of NPD cost estimation and emphasizes the importance of organizational learning and knowledge management (Barão et al. 2017; Dixon 2017; Saadat and Saadat 2016).

The remainder of this chapter is structured as follows: First, we motivate our research through an overview of the existing literature, which will lead to our research questions. Afterwards, we describe the setting of our case study and present our findings in the form of 27 observations. We build on these observations to answer our research questions and discuss the refined insights we provide to the literature. We conclude with a summary, limitations of this study, and an outlook on future research opportunities.

4.2 Literature review

The activities pursued in the development phase of a product are crucial for most companies, as they lead to new products that they can introduce to the market (Artz et al. 2010; Brown and Eisenhardt 1995; Chao and Kavadias 2008; Hauser et al. 2006; Talay et al. 2014). The costs that go along with such activities can represent a significant amount of resources for an organization (Artz et al. 2010; Cooper and Kleinschmidt 1996; Morbey 1988). At the same time, the long, uncertain, and complex process of NPD makes the management of these costs a challenging endeavor (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015). Rising cost pressure, technical disruptions, and increasing competition put additional attention on this task (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). Decision-makers are under pressure to efficiently estimate and allocate resources to development projects, as they are usually limited (Blanning 1981; Case 1972; Chwastyk and Kołosowski 2014; Xiao-chen et al. 2009).

Several authors propose methods especially designed for NPD cost estimation (Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003). The high level of uncertainty, as well as a limited amount of usable data for NPD cost estimation, are shown as major challenges in this context (Harrold and Nicol 1977; Mousavi et al. 2015; Roy et al. 2001). Most of these methods proposed for NPD cost estimation are presented in the context of case study research (Johnson and Kirchain 2011; Love and Roper 2002; Roy et al. 2001). However, as the focus of those studies lies in the presentation of specific NPD cost estimation methods, no special attention is put on the challenges that actually arise in the organizational context.[22]

One methodological approach to estimate NPD costs is the *NPD cost benchmarking method*. This approach consists of two main components: the baseline and the parametric part. The baseline is derived by extracting data from annual reports of relevant competitors to include it in a regression analysis model. This baseline represents the average NPD costs for a development project in the industry. Since development projects differ in complexity, a parametric part is added: Depending on the character of the specific development project, cost drivers increase or decrease the resulting NPD cost estimation. The concept of cost-matrices supplements the method: It is applied to break down the baseline, as well as the cost drivers, to manageable portions. These portions comprise a product's technical components such as modular components used, but also procedural aspects such as different divisions involved in the development process.

To improve our understanding of challenges that arise in the context of NPD cost estimation in actual organizations, we define two dimensions we explore in the context of this case study: credibility and data. The first dimension of special relevance for the challenge of NPD cost estimation is the aspect of a method's credibility within an organization: No matter how accurate a cost estimation is, it will only bring relevant benefits to a company's cost management if people accept it (Prince 2002; Smith and Mason 1997). In this context, we aim to shed light on two aspects. First, we want to investigate how credibility can be improved in NPD cost estimation. The environment of NPD is characterized by a high level of uncertainty, which makes the estimation of the corresponding costs particularly challenging (Chen et al. 2020b; Mousavi et al. 2015; Roy et al. 2001; Santiago and Bifano 2005; Tatikonda and Rosenthal 2000; Zhaodong et al. 2015). The credibility of an approach to face this challenge is an important driver of its success (Prince 2002; Smith and Mason 1997). Scholars that present NPD cost estimation methods present aspects that are relevant to their method's success. Examples are the inclusion of experts, a method's validation, a maintenance process, or the combination of regression and parametric models (Adelberger and Haft-Zboril 2015; Bashir et al. 2006; Bashir and Thomson 2004; Chen et al. 2019; Hamilton and Westney 2002; Heller et al. 2012; Johnson and Kirchain 2011; Li et al. 2009; Relich 2016; Roy et al. 2001; Salam et al. 2009; Scanlan et al. 2006; Sutopo et al. 2013; Yin et al. 2015). However, these studies do not give detailed empirical insights about aspects that actively improve a method's credibility in an actual organizational context.

The second aspect we investigate in the context of the credibility of NPD cost estimation methods is specific to the observed *NPD cost benchmarking method*. We ask for what types of analyses the specific method delivers credible results. The method itself is designed for estimating the NPD costs of a product in the early development phase. This purpose is aligned with the majority of NPD cost estimation methods present in the literature (e.g. Adelberger and Haft-Zboril 2015; Chen et al. 2010; Johnson and Kirchain 2011). However, additional scenarios in which the method might be applied are thinkable. Furthermore, the *NPD cost benchmarking method*'s design is focused on a single product. Therefore, the estimation of components that go beyond a single product, such as modular components, can be seen as a potential weak point of the method. As this method is new to the literature, we build on our empirical study to deliver the first insights on the credibility of this particular NPD cost estimation method.

The second dimension of special relevance for NPD cost estimation is the aspect of data. Any organization confronted with the challenge of NPD cost estimation must build their approach on some kind of data. In practice, this bears several challenges, which we want to investigate. First, we want to investigate the challenges that occur when building an NPD cost estimation method on external data. Most of the existing methods on NPD cost estimation build on a company's internal cost data from previous products (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large

[22] See Chapter 2 for a comprehensive overview about NPD cost estimation methods.

et al. 1976). Few scholars in this context present approaches that go beyond the data boundaries of an organization and also include external data in their approaches (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). However, these approaches do not put detailed focus on the challenges that occur in an actual organization when NPD costs are estimated built on external data. By investigating the *NPD cost benchmarking method* in practice, we want to unveil major challenges in this context.

As the second question in the context of data, we investigate how actual organizations deal with the challenge of poor-quality data in NPD cost estimation. The poor-quality data problem in NPD cost estimation is repeatedly discussed in the literature. Several studies emphasize, that the inclusion of as much quantitative and qualitative data as possible is beneficial for NPD cost estimation (Hamilton and Westney 2002; Roy et al. 2001). In practice though, relevant data to be used in NPD cost estimation is often scarce. The innovative character of NPD, the low frequency of newly developed products, and missing databases are the main reasons for this issue (Carreyette 1977; Chen et al. 2020b; Gebhardt 2017; Harrold and Nicol 1977; Heller et al. 2012; Mousavi et al. 2015; Steck-Winter and Šebo 2008). As previous studies do not investigate in detail, how organizations deal with the challenge of poor-quality data in NPD cost estimation, we ask this question in the context of this case study.

Table 22 summarizes our research questions, structured by the two dimensions credibility and data. We further differentiate between the focus on general insights on NPD cost estimation, and insights that are more specific on the *NPD cost benchmarking method*.

Table 22: Research questions for the practical study on the *NPD cost benchmarking method*

Dimension	**Focus: General insights on NPD cost estimation**	**Focus: Specific insights on the NPD cost benchmarking method**
Credibility	RQ1: How can credibility in methodological NPD cost estimation be improved?	RQ2: For what types of analyses does the *NPD cost benchmarking method* deliver credible results?
Data	RQ3: What are challenges of estimating NPD costs based on external data? RQ4: How do companies deal with data of poor quality in NPD cost estimation?	

4.3 Research design

We had the opportunity to be involved as the *AUTO AG*, an international premium automotive original equipment manufacturer (hereinafter OEM), implemented the *NPD cost benchmarking method* as a new cost management tool. During a three-year residence at the company between 2019 and 2021, the researcher was an active member of the project team within the product controlling department that implemented the method. This key role guaranteed access to all relevant discussions and documents in the context of the company's application of the *NPD cost benchmarking method*. Figure 15 gives an overview about the chronological context of the case study.

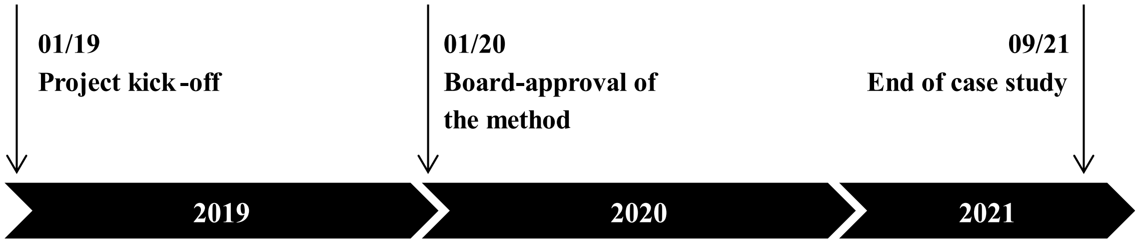

Figure 15: Chronological context of the case study

The approach of long-term interventionist research allowed us to gain deep and valuable insights to ensure a detailed understanding of complex structures and issues (Jönsson and Lukka 2006). The valuable insight of a case study “contributes uniquely to our knowledge of individual, organizational, social, and political phenomena” (Yin 2009). With such a single case study, we will most likely not be able to transfer our findings to any given application case, due to limitations regarding generalizability. However, “a single case can be a very powerful example” (Siggelkow 2007). We also cannot fully exclude a potential bias that comes with this research setting, as the researcher might focus only on insights in favor of his or her initial ideas due to the personal involvement (Norris 1997).

The high level of involvement ensured full access to relevant data on the company and its projects. That data included project cost information as well as communication and documentation in the context of the NPD cost estimation process before, during, and after the implementation of the new method. We also made sure to keep track of all actions and observations during the project period by writing a research diary as suggested by Jönsson and Lukka (2006). To supplement the observations and our document analysis, we conducted a series of informal discussion interviews with key employees involved in the implementation or the application of the method. These interviews were done without a strict structure and had the character of discussions about the method and the interviewee’s perceptions of it.

Table 23 gives an overview of the different data sources we build our study on. As this research is built on confidential data collected at the case company, we disguise sensitive data throughout this work. The names of employees are replaced either by the respective functional roles. Furthermore, we present numerical values at several points, which represent illustrative numbers. We assure, that the magnitude and relation between values are comparable to the actual data obtained at the case company.

Table 23: Overview of data sources for our case study

Source	**Description**
Research diary	85 pages of notes made by the researcher regarding relevant observations, thoughts, and interpretations during the case study
Emails	163 emails representing relevant communication during the case study
Documents	48 PDF, Power-Point, and Excel files covering relevant data, documentation, or analysis
Discussion interviews	7 discussion interviews (approximately 5h in total) with stakeholders that were involved in the implementation and/or application of the method at the *AUTO AG*

The case company *AUTO AG* is a premium automotive OEM with a rich history of developing, manufacturing, and selling vehicles. The company is an individual entity within an international multi-brand group of OEMs. As a premium OEM, the company aims to provide technologically advanced products to its customers all over the world. Like all companies in the automotive sector, *AUTO AG* faces challenges in terms of technological disruptions, new competitors, and rising cost pressure on its products.

Lately, several of the company's products exceeded their NPD cost targets, threatening the profitability of its products. To steer against this development, the product controlling department (hereinafter PC) decided to improve their capabilities in making ambitious and project-specific NPD cost estimations in the early phase of NPD. Before, the process of NPD cost estimation was mainly based on a table of standard costs for certain project types. This table differentiated between different kinds of vehicle projects and had several shortcomings: First, it was based on internal data only. As the company was struggling with rising NPD costs, solely focusing on internal information seemed counterproductive. Second, the table of standard costs was not precise enough to cover project-specific cost structures and often led to unclear premises behind estimations.[23]

To improve the NPD cost estimation capabilities of the company, a project was set up to implement the *NPD cost benchmarking method* as the dominant technique for NPD cost estimation in the early phase of NPD. The implementation of the method was assigned to be in responsibility of this project team, which consisted of employees from PC, but also the technical development division. The team was supported by a management consulting company. The case company implemented the method in Microsoft Excel. However, at a later stage, it should be transferred to another IT solution. The application as well as the maintenance after the implementation was given in the responsibility of a team consisting of members from the PC. The author of this work was actively involved in all the described activities. This allowed us to make a series of observations during these activities. We build on these observations to answer our research questions.

4.4 Empirical test of the NPD cost benchmarking method

In this chapter, we describe the relevant observations gathered during the case study. We later build on these observations to answer our research questions. We describe them along with the method's implementation steps: We start with the baseline derivation, go on with the definition of cost-matrices before we continue with the parametrization. Afterwards, we highlight insights on the activities of validation, introduction, and maintenance of the method, before we describe our observations during its application. We conclude this chapter with observations made regarding three further application scenarios we were able to witness in the context of this case study.

4.4.1 Baseline derivation

At several points during the baseline derivation, challenges occurred that made the *AUTO AG* deviate from the methodological approach of the *NPD cost benchmarking method*. We start with the definition of the development project types (hereinafter DPTs) which represent the main categories of development projects. We follow with the competitor selection and the extraction of public data from annual reports. Afterwards, we describe observations regarding the adjustment of that data, the regression analysis model, and finally the selection of the baseline.

[23] Example: The regions a vehicle is developed for, have a big impact on its NPD costs, as specific regulations must be fulfilled. However, such details were not differentiated in the table of standard costs.

4.4.1.1.1 Definition of development project types

Observation 1: The method requires defining DPTs that are developed by all competitors so that external data from all these competitors can potentially be used. However, the company did not follow this intended approach, as one of the four defined DPTs resembled a rather company-specific product type. This increased the credibility towards the method within the company and the DPTs were *"questioned very little"*, as a project team member from the consulting company remembered. However, we could later observe that this deviation from the method's original design challenged its implementation especially in terms of data availability.

4.4.1.1.2 Competitor selection

Observation 2: The case company included one company in the analysis, that did not resemble a direct competitor. They did this, to have at least one source of data for the company-specific DPT selected earlier. With this decision, significant effort could be saved, for the cost of having only one data source for the company-specific DPT. Few discussions arose regarding the credibility of the selected competitors, also because the case company's top management was strongly involved in the process.

4.4.1.1.3 Extraction of public data

Observation 3: We expected a trade-off between the observation period for data extraction being too long regarding technical comparability and too short regarding statistical significance for the regression analysis models. However, we could observe little to no discussions arising regarding the method's credibility in this context. On the contrary, we observed a common acceptance of the models' results as objective outcomes. We assume this to be the case because the consulting project team members handled this data gathering and the employees *"trusted their methodologically correct actions"*, as a project team member from PC remembered. In this context, the matching between DPTs and products was rather intuitive, and *"only for few vehicles, this was actually challenging since the product architecture clearly defines it"* (consulting project team member).

Observation 4: Although only one competitor could be selected to gather data for the company-specific DPT, credibility was not critically harmed, but rather improved through this decision. This suggests that credibility in NPD cost estimation is not necessarily limited to statistical relationships, but also reactive to other more qualitative aspects.

4.4.1.1.4 Adjustment of public data

Observation 5: The project team decided to pursue two additional adjustment steps that were not in the original scope of the method. They did this, as they were confronted with a high level of skepticism towards the comparability of the external data. Despite this additional effort, the comparability of the external NPD costs and the internal cost structures was *"a huge topic and repeatedly questioned"*, as a project team member emphasized. We could also observe that some stakeholders were having difficulties understanding the steps taken. This marks the comparability between the external and the internal data as one of the most critical aspects of the method's credibility.

The two additional steps to adjust the external public data were taken to include industry- and company-specific premises: adjustment for modular kit structures and adjustment for portfolio effects. In the following, we briefly want to elaborate on these steps.

In the automotive industry, modular kits play a significant role in the cost-efficient development of vehicles (ElMaraghy et al. 2013; Jose and Tollenaere 2005; Pandremenos et al. 2009; Ramdas et al. 2003). Such modular kits are developed to fit into a range of vehicle projects and therefore can reduce the overall NPD costs of the product portfolio. However, developing such structures requires high investments which only pay out once the architecture can be applied to a broad range of products. This implies that a company that spends more for a single modular kit than another one, can still be cost-efficient if it achieves a higher number of vehicles based on that kit. To avoid having such effects distort the cost comparability, the project team included a modular kit efficiency factor, which allowed to compare the cost data of companies that operate with different modular strategies.

The second additional step was implemented to avoid distortions due to company-specific portfolio strategies. The vehicles developed by most companies in the industry cover a wide range of customer segments. From entry products to luxury vehicles, the price position towards the customer varies significantly. As products sold at higher price positions require a higher product substance, costly innovations are often included, making their development more expensive. The project team defined a portfolio factor to avoid having such effects distort the cost comparability.

Despite this effort, one of the project team members mentioned, that the *“baseline could always be questioned regarding comparability”*. This concern was proven right by two main areas of criticism: the process comparability and the understanding of adjustment steps. The first point addresses the issue of the imprecise definition of NPD costs through the industry: *“We cannot know in which structures our competitor works and therefore which activities and costs they define as NPD costs”* (PC manager during a workshop to introduce the method). The second point of criticism addressed the issue of understanding the adjustment steps. An example of this was the modular kit efficiency factor. The raw data before adjustment could show that the competitor spends more money per DPT but still would have a lower cost level per DPT after adjustment. It was difficult for the project team “*to explain that the competitor would pay less for their vehicles if they would follow our modular kit strategy”*, as a project team member from PC noticed.

4.4.1.1.5 Regression analysis model

Observation 6: Few questions were raised regarding the significance of the regression analysis model. This was surprising, especially since doubts regarding the comparability of the external data were regularly raised. This might have been the case because the trust towards the consulting company regarding the correct calculation made nobody seriously question the methodological procedure: *“I believed that the project team carried out the analysis in a correct manner, although it seemed a bit like black magic”* (project team member from PC). During our observations through the entire case study, only one employee questioned that the number of data points included was a rather small sample for a regression analysis.

4.4.1.1.6 Selection of baseline

Observation 7: The selection of a baseline per DPT did not follow any structured procedure as intended by the method but was the result of discussions between top managers.

The comparability between the method’s outcome and the experience from past projects was crucial for the selection of baselines. Due to the definition of the company-specific DPT, only one value was available as a potential baseline. Here, the company did not rely on the method at all, but set a deviant baseline based on their historical cost data. We can see that credibility mostly based on experience seems to be more important in NPD cost estimation than methodological consistency. For the baselines of the remaining DPTs, the company selected values based on the regression analysis. As the values for the competitors did not vary too much, the focus for the project team during the discussions was not to pick the lowest amount possible, but to pick baselines that could be accepted by all stakeholders. Therefore they *“did not really follow an academic approach”,* as a member of the project team reflected. He further noticed that this was necessary for the *“organization to drag along with the method”*. During the discussions, actual NPD costs from past projects or recent cost estimations were used for assessing the different values regarding their comparability to the actual cost structures of the company.

4.4.2 Definition of cost-matrices

The cost-matrices function as the part of the method that individually, per baseline and cost-driver split the estimated NPD costs into manageable portions. In the following, we describe our main observations during the practical implementation of this component.

Observation 8: Instead of defining each matrix individually and making use of the full adaptability of the method, generic matrices were mostly used. As the company did not have a complete database for historical information on this level of detail, this seemed the best way to deal with this issue also regarding the trade-off between effort and accuracy.

The case company did not specify all the more than 120 cost-matrices individually. On the contrary, four distinct matrices were defined in the beginning, one for each DPT, which were the starting points for defining the matrices for each cost driver within those DPTs. As no database within the case company was able to give an overview of the entire cost structure defined by the cost-matrices, the vertical and the horizontal dimension had to be derived separately for each of the four basic matrices. The vertical dimension was defined in the way in which the NPD costs are reported in the company's business cases, including modular components as separate rows. These business cases were analyzed to define the vertical dimensions of the four basic cost-matrices. The horizontal dimension was defined along with the divisions of the technical development. The split between the five divisions varied significantly among DPTs and cost drivers, hence average distributions from past projects were used to calculate the horizontal split individually for each row. After defining the vertical as well as the horizontal split for all four basic matrices, they were multiplied. This led to the four basic matrices for the four DPTs, which were the starting point for defining the set of matrices for the cost drivers while remaining like this for the split of the baselines per DPT. Many matrices were used for several cost drivers and not each matrix had to be defined from scratch.

Observation 9: The lack of available cost data on an adequate level of detail led to the need to have expert discussions per matrix. These required an enormous number of meetings and analytical effort. This time-consuming step often led to a trade-off between effort and accuracy.

The procedure to define the matrices was *"clear and transparent and in the context of the entire method adequate"*, as a project team member recalled. The complex structures of components and functions, modular architectures, and vehicle-specific parts were especially challenging during the definition. A project team member emphasized the fact, that *"we really constructed a complex world in our NPD cost management"*. Therefore, a trade-off between effort and accuracy had to be considered. The cross-functional project team was of special importance here. Experienced project controllers, as well as long-term employees from technical project management, could provide insights from past projects. Despite setting the values, this also increased the credibility of the entire method, as this made sure, that a wide range of relevant data sources and experts were included in the process.

Observation 10: Incorporating modular structures as a dimension of the cost-matrices led to increasing questions regarding the method's credibility. Difficulties in comprehending the idea to estimate NPD costs for modular structures from a single product's cost estimation made this part a steady threat.

Breaking the baseline down to the dimensions of the cost-matrices, made *"the NPD costs as the output of the method comparable"*, an experienced project controller stated. However, some of the components defined for the vertical dimension of the matrices were not vehicle specific, but rather had a modular character. This showed to be challenging for the credibility of the entire method: If we imagine a large modular structure, that is used in several vehicle projects, that structure itself would be a project that has to be controlled and managed as an individual project. As the method uses vehicle projects as its object of estimation, this leads to a potential conflict: As the modular structure itself is part of several vehicle projects, these vehicle projects must incorporate the costs of that structure in their business cases. If they do not, the company risks, that the vehicle projects' revenues cannot cover the overall NPD costs of the company. Following the method, the overall NPD costs for the vehicle project are set and a fraction of that are the NPD costs for the modular structure. Therefore, the method only generates a part of the NPD costs for the modular structure, if not all the vehicle projects using it are estimated. To estimate the entire modular structure, all projects using it would have to be estimated and the sum of the fractions for the modular structure through all vehicle projects taken as estimation for it.

Various employees and managers that got in touch with the method during the implementation or also later during the application questioned the credibility of the method in this regard. As an example, the Chief Financial Officer (hereinafter CFO) of the company questioned *"why the NPD costs for that specific modular structure were that high for that project"*. This topic was seen as a big weakness of the method and one employee in project controlling even described the method as *"not usable"* for such estimations.

4.4.3 Parametrization

In this section, we describe the main observations during the implementation of the last component of the method: the parametrization through cost drivers.

Observation 11: The poor quality of data in NPD cost estimation hindered the process. However, long and effort-taking discussions with experts could solve this issue.

Three steps are necessary to implement the parametric part of this method. First, the cost drivers must be identified, then their possible levels must be set before estimating the quantified NPD cost effects for each of them. It became clear from the beginning, that these steps could not follow a linear procedure at the case company. They rather were the result of long and iterative discussions going back and forth. The involvement of experts from different divisions of the company was of central importance: Deep industry and product knowledge from a technical perspective were crucial and *"very important for the acceptance of the method"* (project team member from PC). This led to vivid discussions, as many ideas came up for additional cost drivers, while the project team had to make sure that only the most relevant ones were included to respect the *"trade-off between complexity and accuracy"*, as one of the project team members emphasized. Putting the effort in these discussions was of *"crucial importance for the acceptance"*, as a project team member from PC justified the process. The final parametric model in the case of the *AUTO AG* covered around 30 cost drivers.

Observation 12: The parametric part of the *NPD cost benchmarking method* was considered a strong driver for the credibility of the overall method. It provides its output with clearly defined premises, which made it easy for stakeholders to understand the numerical output.

The ability to generate NPD cost estimations based on clearly defined premises *"was beneficial for the acceptance within the company"*, as emphasized by a project team member. One of his colleagues emphasized, that *"as a project controller, I frequently get asked which premises are set for my cost estimations. This method allows me to define different complexity levels of development projects with a transparent definition of premises"* and helps us to *"understand where the values come from"*.

The information for the parametric part of the method relied heavily on the internal experience of experts within the case company. This stood in contrast to the external benchmarking character of the baseline definition. This contrast proved to be one of the disadvantages as well as one of the advantages during the implementation. Several managers and employees criticized the fact, that the *"external perspective on the cost drivers, was largely missing"*, as a project team member from PC remembered. However, relying on internal expertise for the parametrization also had a major benefit: By including experts from various departments in the discussions, a wide spread of awareness and knowledge could be achieved early on. As most of these experts would later work with the method, they were already familiar with the cost drivers for the application. The project team was enabled to refer to these experts if specific values were questioned, which showed to be convincing in most cases.

Observation 13: The unambiguous description of each cost-driver was an important driver of the method's credibility.

An insufficient description of cost drivers was a major line of criticism during the parametrization. Examples were questions like *"what exactly is a drive train in the definition of this method?"* or *"how do you define track width?"* from employees that got in touch with the method. It became clear, that the project team had to be very precise in the definition of the cost drivers, to avoid confusion. One of the employees from PC remembered a specific occasion in which the colleagues involved could not make a clear decision regarding the described level to pick for a certain cost driver. The team then picked the one which was closest to their experience regarding its quantified effect on the NPD costs. As this was not how the method should be used, the said colleague criticized the procedure: *"this sucks!"*.

4.4.4 Validating, introducing, and maintaining the method

After the definition of the method's components, the project team took further action to validate the model, but also to spread knowledge about this new method within the case company. Beyond these one-time activities, a sustainable maintenance process was also established. In the following, we will describe the most relevant observations during these activities. We start with the one-time activities of validating and introducing the method and follow with the maintenance process.

Observation 14: The steps of validating and introducing a new NPD cost estimation method in a company are highly relevant for its success. These actions should not only focus on quantitatively showing the validity of a method, but also provide detailed information to improve understanding and credibility among stakeholders.

Observation 15: The effort to validate and communicate the outcome and logic of such a new method, pays off in higher credibility at the time of application.

The company pursued three strings of activities to validate the method as well as to introduce it to the company: the analytical comparison to the existing NPD cost estimation method, a coordinated discussion series with members of the technical project management, and a management training within the PC department.

The first string of activities to validate and introduce the method was the analytical comparison to the existing NPD cost estimation practices. To do this, 15 projects already developed or currently in development were estimated using the new method. The results were then compared to the estimations previously done by the company. The average deviation between these old and new estimations across all 15 projects was 4%. As this deviation was acceptedly low, the analysis worked as a valuable assessment throughout the method's introduction. The value of this analysis could be observed through repeated questions by managers whether the new method stands in conflict with the existing estimations. To show that the existing estimations were not completely off, was *"really important and valuable for the credibility of the method"*, as a project team member from PC confirmed. The ability to have *"clearly defined premises for these estimations"*, convinced the decision-makers of the case company regarding the value of implementing this new method (manager from project controlling during a presentation of the analysis). Although a significant amount of effort was put into this analysis, one of the project team members from PC *"had the feeling that we could have taken more time for this comparison analysis"*.

The second string of activities to validate and introduce the method was a series of coordinated discussion meetings with representatives of the eight technical project management departments. The goal of these meetings was to present the new method to these experts as well as to test its application by estimating actual projects that they were currently working on. This was done to gather coordinated feedback for further improvement of the method as well as to spread knowledge about it within the company. These cross-functional meetings were very helpful for the validation of the method and one of the *"success factors for the credibility of the method"*, as one of the project team members put it. Although some of the experts were critical, the overall feedback towards the new method was positive, as some of the quotes in Table 24 summarize. Significant effort was necessary to organize and carry out these meetings, but as *"such an approach can help us to finally talk less about budgets and more about actual development activities"* (employee from technical development department), all parties involved agreed that this extra round of validation was beneficial.

Table 24: Feedback regarding the *NPD cost benchmarking method* from representatives of the eight technical development project management departments

"In general, we see the implementation of the method and consequently the replacement of the table of standard costs positively."
"Very powerful tool."
"Our current estimation is below that value because we could pursue a higher share of carry-over parts than expected."
"I would endorse that value."
"I am positively surprised. That value fits quite well. The tool seems very helpful in making the first estimation."

The third string of activities to validate and introduce the method was a training regarding the method, which was held with the managers of the PC department. The training was set as a marketplace, where the managers would rotate between posters explaining the components of the method. The focus was less on the numerical outcome, and more on the logic behind each component. Despite general approval of the method, the discussions during this training circled the same topics that we already described during the implementation of the components of the method: the comparability of external values, the adjustment steps as well as the logic behind the cost-matrices regarding modular structures.

After the method was properly validated and introduced to the company, the project team decided that a proper maintenance process was necessary. For this purpose, ongoing activities were defined to keep the method in a current state.

Observation 16: The long-term effort for keeping such a complex method up to date, is crucial for sustainable implementation. As the method is based on internal and external historical data in connection with expert knowledge, new information should regularly be included to avoid a loss of accuracy.

The components of the method are based on a variety of data from different sources. Innovative development processes and technological changes are common in NPD. Regular maintenance activities are necessary to keep the data included in the method up to date. As the fluctuation regarding data differs between the method's components, varying maintenance intervals are reasonable. The baseline as a result of the regression analysis is not subject to rapid change. The case company decided that the baseline is to be updated every two to three years. An annual re-calculation was discussed, but considered not to be efficient, as only one additional year of data could be included in the analysis. The effect on the results of the regression analysis would most likely not be significant and therefore the additional effort seemed not beneficial for the case company.

Regarding the cost-matrices and the cost drivers, the project team proposed and implemented a rather different approach: *"It will be super important to keep the cost drivers up to date"*, as a product controller emphasized. This highlights the fact that the cost-matrices and especially the cost drivers are subject to constant changes as technical innovation and adjustments in development processes must be considered. Therefore, a team of employees was made responsible to keep the components of the method up to date. During their bi-weekly meetings, the maintenance team discussed all change proposals brought up during the method's applications to decide whether and how to incorporate them. In order not to mix up different versions of the method, the maintenance team released an update once a significant number of adjustments were done. During the observation period of the case study, this happened twice.

4.4.5 Application scenario 1: Long-term project-level NPD cost estimation

After the *NPD cost benchmarking method* was implemented at the *AUTO AG*, it played a crucial role in the NPD cost estimation process. The method was designed and implemented as a tool to estimate the NPD costs of a new product in the early phase of its product life cycle. We call this application scenario 1: Long-term estimation scenario on project-level. This application scenario is set at the very beginning of a development project, at the decision of whether to pursue a product idea or not. For this purpose, an initial business case is set up that represents the product's revenues and a full cost perspective of variable and fixed costs. Figure 16 shows the simplified structure of a vehicle's business case as an example. At the time of this evaluation, the project characteristics and cost objects are highly volatile in most cases. This applies especially to the position of NPD costs due to the uncertain character of new product development activities. However, it is necessary to include an NPD cost estimate for the management to decide on a full cost perspective. For this purpose, the method was applied.

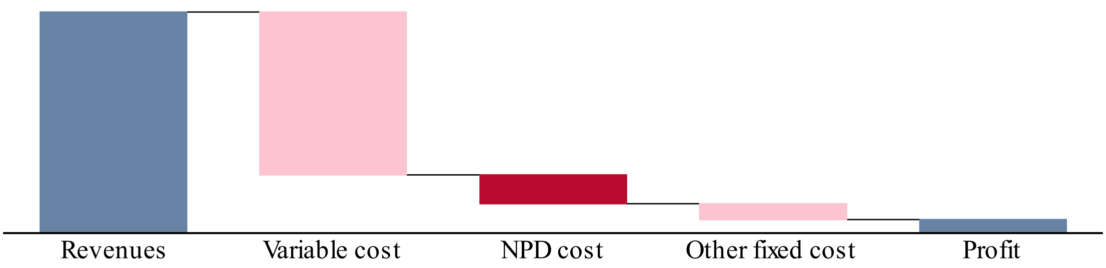

Figure 16: Exemplary business case of a vehicle project

Observation 17: The method functions as a valuable tool aiding early-phase product management in long-term and project-specific NPD cost estimation. The application of the method for such estimation scenarios can be seen as the purpose it was designed for.

The method's application in such a scenario could be observed on several occasions, as this analysis had to be done every time a new development project emerged. One employee from project controlling confirmed the successful application of the method in new projects: *"We use this method a lot within this project at the moment"*. One of his colleagues also confirmed that the method was applied within one of the projects he was responsible for, *"in the classical manner in which the method should be applied"*. The application itself required "*little effort"*, as stated during one of the interviews with an employee from PC.

The estimation process in the early project phase is characterized by cross-functional discussions. The value of having this method within these discussions was emphasized by an employee of the PC department: *"It was very good, that I had the tool with me. The experts confirmed, that only certain aspects had to be adjusted for the vehicle project so having an estimation for that adjustment was definitely valuable"*. During the early phase of development, many premises of the development project are not fully defined yet. The parametric part of the method allows an estimation of different options regarding product architecture. Therefore, it is *"good for an estimation at project start as we can play with the premises"*, as described by an employee from PC during a discussion interview. This makes the method *„very helpful for the early phase"*, as he continued. The method also enabled the product controllers to do a *"compliant documentation of the origin of cost estimations"*, as one of them emphasized.

Observation 18: The high level of uncertainty in NPD repeatedly led to missing product information during the application in long-term and project-specific NPD cost estimation scenarios.

Although the cost-drivers were designed to be based on observable product-premises at the early product stage, expert guesses were necessary at some points. Setting the right levels for the cost drivers led to two types of discussions: First, in some cases, the information to set some premises was not known to the employees involved leading to the necessary involvement of further experts and consequently to an inefficient cost estimation process. Second, some premises were not defined yet for the projects to be estimated. In such cases, an assumption had to be made for reconsideration at a later stage.

Observation 19: In some cases, project managers could not be convinced that the outcome of the method resembled a valid estimation. The reason for such a rejection was usually a significant deviation between the estimate and the personal experience of decision-makers. One employee from the technical project management insisted, that he *"could develop a project for far less than that"* and concluded that it was *"a pity"* as he hoped that the tool would actually help.

Observation 20: Regularly, the estimation of modular components as a result of the cost-matrices was not considered a credible estimation value. The new and abstract way of derivation was usually named as the reason for this. Instead, existing estimations or values from predecessor projects were regularly used for business cases. One employee from the PC department emphasized that the estimations for modular structures are *"simply not tangible"* within the method and were therefore not used.

4.4.6 Three further application scenarios

In the previous section, we described application scenario 1 as a long-term and project-level application of the *NPD cost benchmarking method*. Although the method was originally intended specifically for that kind of estimation, the case company rapidly started to apply the method in other scenarios. This gave us the chance to gather further insights about the method's credibility in different situations. Based on these insights, we could evaluate the method in a more nuanced way and deliver a guide to a reasonable application. In the following, we present three additional application scenarios. We differentiate the original application scenario 1 and the three additional scenarios in a temporal perspective (long-term vs. short-term) and a scope dimension (project vs. portfolio). The object of estimation for this method is always a single development project. However, by doing this at different points in time or by combining estimations for several projects, the method can function as a tool for a range of analyses. Figure 17 puts the four application scenarios into the context of these perspectives.

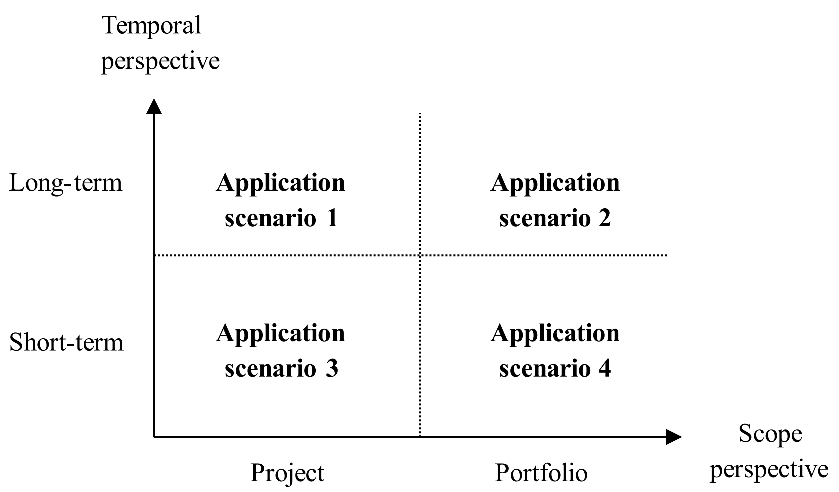

Figure 17: Distinction between temporal and scope perspective for the four application scenarios

From a temporal perspective, we differentiate between short- and long-term types of analyses. Vehicles usually need several years of development before they are ready for production. The method's application in the early product phase is equal to estimating costs that will occur several years in the future, therefore in a long-term perspective. However, it is also possible to use this method to estimate project costs that are expected sooner. We consider the NPD cost estimation of products that are already further in their development process as a short-term perspective.

From a scope perspective, we differentiate between project- and portfolio analyses. Project perspective means using the method to estimate the NPD costs of a single project. In this case, the method is used for a standalone analysis of a single project without any regard for other development activities within the company. When we talk about portfolio perspective, we mean analyses in which the company applies the method to analyze NPD costs within a bigger context. Here, the focus is not on the estimate for a single project, but on the overall sum through the product portfolio on the company- or divisional level. In such scenarios, the method would still have to be applied to each single NPD project which is part of the relevant portfolio, but not the single estimation would be of relevance, but the focus would be on the overall sum.

In the following, we describe each of the three further application scenarios, including relevant observations that help us to evaluate the *NPD cost benchmarking method* for its credibility in different estimation situations.

4.4.6.1 Application scenario 2: Long-term portfolio-level NPD cost estimation

Application scenario 2 represents the long-term and portfolio-level application of the method. On annual basis, the PC department of the *AUTO AG* conducted a strategic portfolio analysis for a long-term projection of the NPD resources necessary. For this purpose, the NPD costs for all projects were estimated and then compared to the budget to assess the financial fit of the planned product portfolio. This procedure represents a typical bottom-up approach to compare the sum of separate cost positions with the overall amount available (Kramer and Hartmann 2014).

Lately, the company had difficulties to fulfill the required development activities while sticking to the NPD budget. To prevent damage to the company's product portfolio, the CFO of the *AUTO AG* asked the PC department for *"arguments, that we work efficient and benchmark-oriented"*. Prior, simplified forecast analyses were used to answer these kinds of questions. Now, the new *NPD cost benchmarking method* was included in the analysis to make sure that cost estimations within the strategic planning were on an efficient and competitive level. This direct link between NPD costs on the company level and project portfolio was *"revolutionary"* to the company, as an employee from PC described it.

The result of the analysis is illustrated in Figure 18. The three lines show the NPD budget (black), which represents the available resources, the annual NPD costs as estimated with the method (red), and the annual NPD costs as calculated following the old procedure before the implementation of the method (blue). The number of development projects for each year was also included to highlight the link between NPD costs and the vehicle portfolio (grey bars).

The analysis predicted issues for the years 2023 to 2025, as the estimation based on the method strongly exceeded the available NPD budget. This led to changes within the project portfolio as well as an increase in the NPD budget. The latter seemed impossible before the analysis, but due to the methodological proof that the portfolio's NPD cost estimation is on a competitive level, additional resources could be allocated. The fact that crucial decisions for the company's product portfolio were made based on the application of the method supports its credibility and applicability in this scenario.

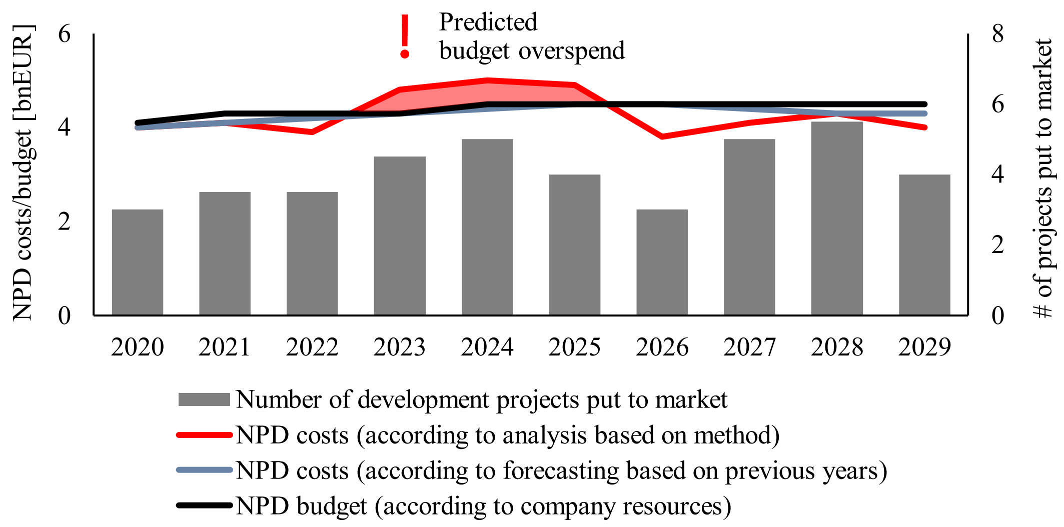

Figure 18: Results of the long-term portfolio analysis based on the method as application scenario 2 (disguised data)

The analysis was used during key discussions with members of the top management. It was not only included in an information package regarding the NPD budget situation handed to the chief executive officer, but also discussed with the head of *AUTO AG's* product strategy. The latter emphasized the value of this analysis: *"I was aware that we would probably exceed the NPD budget during the next ten years, but so far, we were never able to clearly show and quantify that"*.

Observation 21: Applying the *NPD cost benchmarking method* on a larger scale on portfolio-level showed to be the ideal approach to support long-term portfolio decision-making. Several shortcomings that appeared to be threatening on project-level are less significant in this scenario, due to the lower expectation towards accuracy.

Observation 22: The estimation of modular components on portfolio level was considered credible in this specific scenario. Summing up all modular development costs for all projects to construct an overall cost estimation for the development of all these parts could convince the stakeholders.

Observation 23: Missing information regarding premises for certain projects did not threaten the overall analysis. An employee from PC remembered in this context, that *"within such strategic analysis, the claim of accuracy has to be laid down to a certain degree"*.

4.4.6.2 Application scenario 3: Short-term project-level NPD cost estimation

Application scenario 3 represents the usage of the method within the short-term NPD budgeting process for single projects. The case company found itself in a situation, in which the expenses planned for the NPD projects in the upcoming year exceeded the available resources of the company. The PC department decided to involve the new method in the corresponding budgeting discussions. First, all vehicle projects that requested NPD budgets in the next year were identified. Afterwards, these projects were estimated with the method. That estimation was then split into the years of the development cycle, to allow the discussion of a single year. During the discussions, these analyses functioned as a value to challenge the spending plans for the next year. Figure 19 shows exemplary how this was illustrated for each of the projects. We can see how the NPD budget requested for the year 2021 (dark red bar) exceeded the NPD cost estimation proposed using the *NPD cost benchmarking method* (black line). This deviation was used as a discussion starter to challenge the spending plan for the upcoming year.

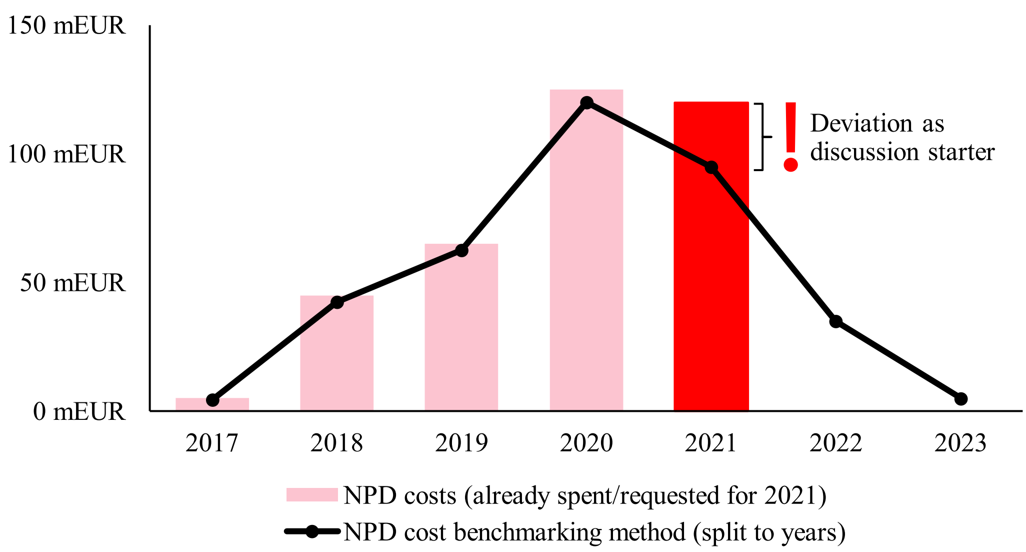

Figure 19: Illustration of requested NPD budget versus the estimation based on the method as application scenario 3 (disguised data)

Observation 24: The application of the method for short-term project estimation turned out advantageous in terms of reduced uncertainty. All information regarding the levels of cost drivers was available, so the method could be fully applied.

Observation 25: We did not observe the method to be a credible source of information regarding managerial decision-making in a short-term scenario on a project-level. Since the projects that were estimated were already far in their development process, project-specific challenges, technical changes, or market demands had already occurred. These aspects could not be fully incorporated into the method's estimation procedure. However, the method's output could still function as a discussion starter to identify cost reduction potential.

The range of reactions towards the use of the method in this scenario strongly differed. While some saw an *"overall positive contribution to the discussions"*, such as a member of the method's implementation project team, a manager of the PC questioned, *"whether such a theoretical model really brings clarity"*.

Crucial for the application of the method when challenging project-level NPD costs was the selection of the right projects. Although sufficient information about the products was available in all cases, it became clear early on, that it only made sense to use the method's estimations to challenge those few projects that were not too far in their development cycle: *"As projects are constantly changing, a retrospective estimation is always difficult"* and the *"method is not to be applied as soon as a project differs from the regular development process"*, as a product controller remembered.

The analysis itself could show three outcomes: Either the requested resources for the next year were lower, similar, or higher than the *NPD cost benchmarking method*'s estimation. In cases in which they were lower or similar, the discussions were usually very short, as the projects did not seem to have the potential for further cost reductions. In cases in which the planned resources were substantially higher than the cost estimation according to the method, more intense discussions arose. Several projects could be identified that planned excessive resources for the upcoming year compared to the estimation. These projects were identified and then specifically investigated for cost reduction potential. Like this, substantial reductions in NPD cost plans could be achieved. One employee from PC attested that the activities *"actually worked quite well back then"*, not without surprise. The primary goal was to identify projects with cost reduction potential and discuss them. Like this, the responsible managers *"had to argue why that deviation existed"*, as a product controller described. These discussions then led to more detailed analyses and often to the identification of project parameters that could be changed to achieve a cost reduction. In this sense, the method helped as a tool for the identification of cost reduction potentials.

4.4.6.3 Application scenario 4: Short-term portfolio-level NPD cost estimation

Application scenario 4 represents the short-term estimation of development portfolios per division. The vehicle project management at the *AUTO AG* was structured in three divisions, the vehicle divisions. Additionally, four project management divisions were responsible for modular structures, which we call the module divisions. For these seven divisions, annual budgets for NPD costs were to be defined, separately for each of the next three years. To generate the numbers for this new steering mechanism, the PC followed three steps. First, they estimated the overall NPD costs of all relevant vehicle projects per division with the new *NPD cost benchmarking method*. As some of the projects under consideration were already far in their development cycle, the application of the method was considered not appropriate for them. For those projects, existing and established NPD cost estimations were used. In the second step, they broke these values down to years of development using cost curves. In a third step, the NPD cost estimations for modular structures within the estimations were transferred to the module divisions. This distribution was done using assumptions based on historical data. The relevant values for the NPD budget were the sums on the divisional level, while the budgets between projects could be shifted within a division. Table 25 gives an illustration of the way the budgets were set and communicated. For simplicity reasons, we assume that the three vehicle divisions develop two projects each.

Table 25: Illustration of estimated budgets per year as result of application scenario 4 (disguised data)

	2020	2021	2022
Vehicle division 1	**30 mEUR**	**29 mEUR**	**5 mEUR**
Vehicle project 1	*10 mEUR*	*15 mEUR*	*2 mEUR*
Vehicle project 2	*20 mEUR*	*14 mEUR*	*3 mEUR*
Vehicle division 2	**9 mEUR**	**23 mEUR**	**10 mEUR**
Vehicle project 3	*8 mEUR*	*9 mEUR*	*5 mEUR*
Vehicle project 4	*1 mEUR*	*14 mEUR*	*5 mEUR*
Vehicle division 3	**45 mEUR**	**80 mEUR**	**70 mEUR**
Vehicle project 5	*35 mEUR*	*65 mEUR*	*40 mEUR*
Vehicle project 6	*10 mEUR*	*15 mEUR*	*30 mEUR*
Module division 1	**10 mEUR**	**8 mEUR**	**9 mEUR**
Module division 2	**11 mEUR**	**16 mEUR**	**15 mEUR**
Module division 3	**49 mEUR**	**40 mEUR**	**51 mEUR**
Module division 4	**30 mEUR**	**25 mEUR**	**26 mEUR**

Observation 26: The estimation of ongoing development projects in a portfolio did not show to be credible due to project-specifics that could not be considered by the method. Nevertheless, some projects still at an early stage could be estimated by the method making it at least partially credible. Eventually, this led to only about ten percent of the values of the vehicle projects for the next year coming from the method.

Observation 27: We could see that the method has severe shortcomings regarding the estimation of modular structures. Experts had to be included in improving the output of the method. Like this, the method could only propose a starting point for this kind of analysis but was independently not appropriate for large parts of this estimation scenario.

The basic idea about the derivation of the modular divisions' budget was, that the sum of NPD cost portions for modular structures through all vehicle projects must resemble the overall spending on modular structures on the company level. In the next step, the amount of expenses, that will not be covered by the company's vehicles but the group companies' vehicles, was added to account for all required resources of the scheduled development activities. In the last step, these costs were split into divisions and years based on historical data and experts' premises.

The complexity of this process was challenging for many stakeholders. One employee from PC responsible for the controlling of a module division said that he *"cannot explain to anyone where these numbers come from"*. In general, the idea of linking budgets for the module divisions and the vehicle division was desired by all stakeholders: *"We need that link to steer efficiently"*, as one employee from PC put it. Still, the way the method was used to create that link did not seem appropriate. Due to the differences in vehicle development and modular development and the lack of connection between already known technical challenges or development plans, we recommend the method to be supported by additional approaches in such scenarios.

4.4.6.4 Comparing the application scenarios

The different application scenarios showed that the method can be a valuable tool for the NPD cost management of a company. However, it became obvious that the positive impact varies significantly through the scenarios. Based on the empirical data obtained through observations, interviews, and analysis of various documents, we evaluate the method's credibility in the four application scenarios. An overall trend showed that the method is more credible in the long-term perspective, while it is often not reliable on the short-term. Despite the method being designed for project-level estimations, even higher credibility in analyses on portfolio level could be seen. The estimation of modular components regularly led to challenges in the method's credibility. Figure 20 summarizes our evaluation regarding the method's credibility in different scenarios.

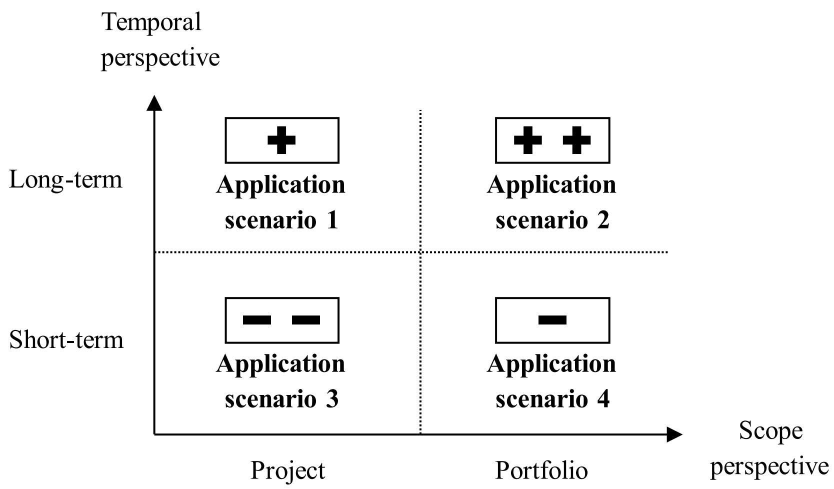

Figure 20: Credibility-assessment of the method in the four application scenarios

4.5 Discussion

In the following, we provide refined insights on NPD cost estimation along with our research questions. We build on the observations described in the previous chapter. Table 26 summarizes the status of the literature, the relevant observations per research question, and the seven contributions to the literature based on this study.

Table 26: Summary of the case study's refined insights to the literature in the context of our research questions, the previously existing insights, and the relevant observations made

Research questions (*Focus* | *Dimension*)	**Existing insights**	**Relevant observations**	**Refined insights based on this study**
RQ1: How can credibility in methodological NPD cost estimation be improved? (*General* | *Credibility*)	The high level of uncertainty and scarce amount of data make NPD cost estimation challenging (Chen et al. 2020b; Mousavi et al. 2015; Roy et al. 2001; Santiago and Bifano 2005; Tatikonda and Rosenthal 2000; Zhaodong et al. 2015). A credible approach is necessary for effective cost management (Prince 2002; Smith and Mason 1997). No detailed empirical investigation on ways to improve credibility in NPD cost estimation is available.	1, 2, 4, 7, 14, 15, 16	(1) The credibility of an NPD cost estimation method can effectively be improved if its implementation is accompanied by active change management.
	The combination of regression and parametric models is a common technique in NPD cost estimation (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). No detailed empirical investigation is available providing insights on the credibility of this approach in actual organizations.	3, 12, 13	(2) The combination of regression and parametric model improves credibility, as the estimation has a well-suited level of explainability for the estimation environment.
RQ2: For what types of analyses does the *NPD cost benchmarking method* deliver credible results? (*Method-specific* | *Credibility*)	The *NPD cost benchmarking method* is designed to estimate the NPD costs of a single product in the early development phase, which is aligned with the majority of NPD cost estimation methods described in the literature (e.g. Adelberger and Haft-Zboril 2015; Chen et al. 2010; Johnson and Kirchain 2011). It is unclear, how the method's credibility is perceived in actual organizations in the context of this original application scenario as well as other potential areas of application.	17, 19, 21, 22, 24, 25, 26	(3) The application with a focus on the long-term NPD cost management of a development portfolio is the most credible application scenario of the method. The short-term application is not recommended.
	Modular product structures are highly relevant for many industries (ElMaraghy et al. 2013; Jose and Tollenaere 2005; Ramdas et al. 2003), but their cost management is a challenge for many organizations (Marion and Meyer 2018; Skirde et al. 2016; Stadtherr and Wouters 2021). Estimation of modular components is a potential weak point of the *NPD cost benchmarking method* due to its product-centered approach. It is not known yet whether this potential weak point applies to the method's application in actual organizations.	10, 20, 27	(4) The estimation of modular components is empirically confirmed as a major weak point of the method. We do not recommend solely using the method for this purpose.

Table 26: Summary of the case study's refined insights to the literature in the context of our research questions, the previously existing insights, and the relevant observations made (continued)

Research questions (*Focus* | *Dimension*)	**Existing insights**	**Relevant observations**	**Refined insights based on this study**
<u>RQ3</u>: What are challenges of estimating NPD costs based on external data? (*General* | *Data*)	The majority of methods for NPD cost estimation builds on internal data from an organization's previous products (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). Few scholars build their NPD cost estimation methods on external data, without emphasizing on the practical challenges that actual organizations are confronted with following such an approach (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b).	5, 6, 15	(5) The comparability problem is the main challenge for the use of external data in NPD cost estimation.
<u>RQ4</u>: How do companies deal with data of poor quality in NPD cost estimation? (*General* | *Data*)	Data of poor quality is repeatedly named one of the biggest challenges in methodological NPD cost estimation (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). No detailed empirical investigation on the magnitude of this challenge in practice is available though.	6, 8, 18, 23	(6) Stakeholders involved in NPD cost estimation are aware of the issue of poor-quality data in NPD. This leads to lower expectations towards the availability of data, making the aspect less problematic than expected.
	Expert knowledge plays an important role in NPD cost estimation (Adelberger and Haft-Zboril 2015; Holtta-Otto and Magee 2006; Riedrich and Sasse 2005; Roy et al. 2001; Scanlan et al. 2006). However, no empirical investigation is available on the role of expert knowledge in the context of poor-quality data in NPD cost estimation.	9,11	(7) Data of poor quality in NPD cost estimation can sufficiently be replaced by expert knowledge.

RQ1: How can credibility in methodological NPD cost estimation be improved?

The first contribution of this study is the realization that the credibility of an NPD cost estimation method can effectively be improved if its implementation is accompanied by active change management.

According to the literature, only a methodological cost estimation approach that delivers credible outcomes can improve the cost management abilities of an organization (Prince 2002; Smith and Mason 1997). The estimation of NPD costs is especially challenging, mostly due to the high level of uncertainty and the scarce amount of comparable data (Chen et al. 2020b; Mousavi et al. 2015; Roy et al. 2001; Santiago and Bifano 2005; Tatikonda and Rosenthal 2000; Zhaodong et al. 2015). However, the existing literature does not present detailed empirical insights about ways to improve an NPD cost estimation method's credibility in an actual organizational context.

Our empirical observations emphasize the importance of activities that go beyond simply introducing an NPD cost estimation method to a company. Only when such a method is properly communicated, adjusted to the company's specific needs, and regular activities for keeping it up to date are made, a sustainable improvement of cost management capabilities can be achieved. In this context, we find that soft factors like proper communication explaining a method's work mechanisms, are nearly as important as the method itself.

We propose active change management as a way to improve the credibility of a new NPD cost estimation method. Implementing a new cost estimation method in the company-specific and flexible environment of NPD often resembles major changes in organizational processes. The empirical findings of this study point to the necessity of active change management when new cost management tools are introduced in this environment. As effective communication, alignment with organization's strategy, and the role of leadership have shown to be relevant drivers of success in change management activities (Burnes and Jackson 2011; By 2005; Gill 2002), we highly suggest including such activities when new methods for NPD cost estimation are introduced to a company.

As the second contribution of this study, we could empirically show, that the methodological combination of regression analysis models and parametric methods improves the credibility in NPD cost estimation, as the estimation approach has a well-suited level of explainability for the estimation environment.

Combining regression models and parametric approaches for NPD cost estimation purposes is an established concept in the literature (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). However, existing studies do not provide detailed empirical evidence about the way this combination improves the credibility of NPD cost estimation in practice.

Our observations suggest that a method's credibility is higher when its users can easily understand how the methodological estimation is derived. At the same time, the methodological procedure benefits from a certain level of objectivity to assure a consistent cost estimation procedure through an organization. We see that these two requirements play a particularly important role in NPD cost estimation since each product and the corresponding estimation is highly uncertain but also very individual due to the innovative character of product development. The combination of regression analysis models and parametric methods is of special relevance in this environment. While a regression model is usually based on statistical relations within past data, a parametric model in this context allows to include very specific and future-oriented aspects more tangibly. With this combination, the users can link product-specific parameter values with the objectivity of a regression model. This leads to an appropriate level of explainability for the users. Therefore, we empirically support the credibility of this idea for organizational NPD cost estimation.

The explainability of the output of a cost estimation method is of big importance for its credibility among stakeholders (Prince 2002; Smith and Mason 1997). Complex cost estimation techniques, for example, based on artificial intelligence, can provide higher accuracy but often at the cost of lower understandability (Cavalieri et al. 2004; Loyer et al. 2016; Verlinden et al. 2008). Such approaches are also applied for NPD cost estimation (Mousavi et al. 2015; Relich 2016; Wu et al. 2012; Yin et al. 2015). However, based on the insights of our study, we can see that a clear understanding and the ability to explain the outcome of an NPD cost estimation method is of high importance in this particular estimation environment. We conclude that the combination of regression analysis and parametric method is a good fit for the product-specific and dynamic environment of NPD, due to the well-suited level of explainability.

RQ2: For what types of analyses does the NPD cost benchmarking method deliver credible results?

As the third contribution of this study, we unveil the long-term NPD cost management of a development portfolio as the most credible application scenario of the *NPD cost benchmarking method*. The short-term application is not recommended.

The *NPD cost benchmarking method* is originally designed for estimating the NPD cost of a single product in the early development phase. With this objective, the approach is aligned with the majority of NPD cost estimation methods described in the literature (e.g. Adelberger and Haft-Zboril 2015; Chen et al. 2010; Johnson and Kirchain 2011). However, the application for other estimation scenarios is thinkable, such as during later stages of a development project, or for analyses on portfolio level. As this work is the first study to empirically describe the practical challenges of the *NPD cost benchmarking method*[24] in an actual organization, no insights are currently available about the method's credibility for different types of estimation scenarios.

Our observations suggest that the method delivers credible estimations on the long-term, while it suffers credibility in short-term analyses, which is why we do not recommend using it for such estimation scenarios. We also find that the method has higher credibility for estimations on the portfolio- compared to the product level. We evaluate the method's credibility based on the observations made and data collected during our case study including four distinct estimation scenarios differentiated in temporal and scope perspective. From a temporal perspective, the method delivered credible results in long-term application scenarios, while it suffers functionality on the short-term: Technical challenges, or changes in product concepts that naturally occur at later stages of a development project, can never fully be included in the method's estimation approach. From a scope perspective, the method showed credible results in portfolio- as well as project-oriented estimation scenarios. Portfolio-centered analyses however show to be the preferred application scenario, as the expansion to portfolio-perspective matches some of the method's shortcomings with lower expectations towards accuracy.

The preferred application on the long-term portfolio level makes the *NPD cost benchmarking method* an ideal tool for long-term planning activities within an organization. Although it is often challenging to foresee the distant future, methodological approaches that support decision-making help companies to develop a sustainable strategy under the condition of uncertainty (Fairholm and Card 2009; Feurer and Chaharbaghi 1995; Peter and Jarratt 2015). We recommend the *NPD cost benchmarking method* as such a tool and propose it to be a fine addition for the organizational toolset on strategic planning and especially the development of a product portfolio strategy.

The fourth contribution of this study lies in the empirical confirmation that the estimation of modular components is a major weak point of the *NPD cost benchmarking method*. We do not recommend solely using the method for this purpose.

Modular product architectures are highly relevant for many industries (ElMaraghy et al. 2013; Jose and Tollenaere 2005; Ramdas et al. 2003), but their cost management is often challenging (Marion and Meyer 2018; Skirde et al. 2016; Stadtherr and Wouters 2021). The estimation of modular components was previously identified as one of the potential weak points of the *NPD cost benchmarking method*: Since the method estimates NPD costs for a single product, but modular components are shared across multiple products, difficulties in cost management may arise. As this work is the first study to empirically describe the

[24] See chapter 3 for more information about the *NPD cost benchmarking method*.

practical challenges of the *NPD cost benchmarking method* in an actual organization, no insights are currently available about the method's credibility for the NPD cost estimation of modular components.

Our observations suggest that the estimation of modular components based on the method is not credible. The method is designed to estimate the entire NPD costs of a product, but exclusively from a single product perspective. This makes several transfer steps necessary to estimate the NPD costs for specific modular structures, which are shared across a range of products: First, the NPD costs of all products using a specific modular structure have to be estimated. Second, the portion of each estimate must be defined which individually accounts for the NPD costs of a specific modular structure used within that product. In the third step, these individual values must be summed up to result in a valid NPD cost estimation for a specific modular structure. Our observations show that these steps are too abstract and depend on too many premises to deliver credible results in an actual organizational context. We conclude that the method is not a credible tool to estimate the NPD costs of single modular components. The method's application should focus on the estimation of components that are exclusively developed for a specific product. Regarding the NPD cost estimation of a product's modular components, we strongly suggest reconsidering the method or supporting the estimation of modular components within products through additional, more refined approaches.

RQ3: What are challenges of estimating NPD costs based on external data?

The fifth contribution of this study is the unveiling of the comparability problem as the main challenge for the use of external data in NPD cost estimation.

Most methods for NPD cost estimation build on internal cost data from an organization's previously developed products (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). To expand beyond this internal focus of NPD cost estimation, few scholars also build their NPD cost estimation methods on external data, such as publicly available product cost information (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). However, neither of these studies put special emphasis on the actual challenges that organizations are confronted with, when building on external data for NPD cost estimation purposes.

Our observations show that the *NPD cost benchmarking method*, as one example of an approach building on external data, can be functional for NPD cost estimation purposes. However, we could also see the main challenge of such approaches: the comparability between internal and external NPD costs. We unveil the comparability problem as the main challenge for the use of external data in NPD cost estimation. The benefit that external data can bring in the sense of competitive cost estimation, is confronted with varying definitions of NPD costs between companies. While methods that exclusively build on internal data can avoid this issue to a large extent (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976), it will always remain challenging to gain full transparency when comparing NPD cost data between companies.

The importance of comparability is in line with insights from inter-company benchmarking activities in general, where comparability is a crucial prerequisite for interpretable analyses (Bhutta and Huq 1999; Markin 1992; Shetty 1993). We conclude that NPD cost estimation methods based on external cost data must include reasonable adjustment steps to react to the comparability problem. However, full comparability in the context of NPD cost estimation based on external data will most likely never be achievable due to the highly company-specific process of NPD.

RQ4: How do companies deal with data of poor quality in NPD cost estimation?

The sixth contribution of this study lies in the way the issue of poor-quality data is perceived in actual organizational NPD cost estimation. Data of poor quality in this context relates to data scarcity in general, but also to data that does not fulfill quality requirements either because of insufficient comparability or its inadequate level of granularity. We find that stakeholders involved in NPD cost estimation are highly aware of the issue of poor data quality for this purpose, which leads to lower expectations in this regard, making the aspect less problematic than expected.

Data scarcity is repeatedly named one of the biggest challenges in NPD cost estimation (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). The innovative character of projects in NPD and therefore low comparability between projects and the corresponding cost data is the main reason for this (Roy et al. 2001; Salam et al. 2009). Although the challenge of poor-quality data for NPD cost estimation is repeatedly brought up in the literature, empirical insights evaluating the problem's actual magnitude are missing so far.

Our observations confirm that the scarce amount of high-quality data usually available for NPD cost estimation is an essential part of this cost management environment (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). However, we find that this obstacle meets lower expectations towards the amount of usable data. As a lacking amount of high-quality data is a constant companion in this environment, people involved in NPD cost estimation develop a certain acceptance towards this issue and find ways to deal with it. We conclude that the low amount of usable data in NPD cost estimation is a challenge, but not as critical as often assumed.

The acceptance of data scarcity in NPD cost estimation is a natural human behavior, as stakeholders are faced with inevitable facts. Previous research in the fields of knowledge management and philosophy argues that uncertainty is a natural part of life and is therefore perceived differently between people that are used to a certain environment and those that are not (Douglas 2001; Li et al. 2013). The insights from our case study in the context of NPD cost estimation are therefore consistent with more general findings regarding human nature.

The seventh contribution of this study is the empirical finding that data of poor quality in NPD cost estimation can sufficiently be replaced through expert knowledge.

NPD cost estimation methods usually build on a wide range of data from different sources. However, these requirements are often confronted with a limited amount of usable data available in actual organizations (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). While we know that expert knowledge plays an important role in NPD cost estimation (Adelberger and Haft-Zboril 2015; Holtta-Otto and Magee 2006; Riedrich and Sasse 2005; Roy et al. 2001; Scanlan et al. 2006), no empirical investigation is available on the role of expert knowledge in the context of poor-quality data in NPD cost estimation.

Our empirical observations show that expert knowledge can sufficiently replace missing or poor-quality NPD cost data in practice. Although this strategy requires major effort extracting tacit knowledge, often this is the only way to solve the challenge. The inclusion of experts has the potential of other positive effects: As knowledge about a cost estimation method is spread and stakeholders in NPD cost management are included during the setup of a method, active change management can be incorporated more efficiently.

The necessity to include experts for filling data gaps in NPD cost estimation raises awareness for a company's learning processes and knowledge management in general. Authors have shown that sustaining tacit knowledge is crucial for a company to learn as an organization (Barão et al. 2017; Dixon 2017; Saadat and Saadat 2016). Our study emphasizes the importance of such activities in the context of NPD cost management. As the involvement of experts for cost estimation purposes requires a significant amount of effort, proactive measures to conserve knowledge within a company can improve its abilities to handle poor-quality data in this context.

4.6 Conclusion

The current literature has unveiled the increasing importance of NPD cost estimation: Due to rising cost pressure and increasing competition, efficient resource allocation is crucial for sustainable economic success (Adelberger and Haft-Zboril 2015; Relich 2016; Riedrich and Sasse 2005). However, most cost estimation methods still do not look at the type of NPD costs in specific, but rather focus on overall product cost or direct material cost (e.g. Adeli and Wu 1998; Altavilla et al. 2018; Kitchenham et al. 2007; Niazi et al. 2006; Ruffo et al. 2006; Ruffo and Hague 2007). Some authors have contributed to this gap, mostly presenting NPD cost estimation methods in the context of case study research (Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003). The detailed challenges of NPD cost estimation in actual organizations though are largely neglected and empirical qualitative studies in this environment are missing.

In our case study, we describe the implementation and application of the *NPD cost benchmarking method* to increase the understanding of challenges in NPD cost estimation. The author of this work took an active role in the implementation, application, and maintenance of said method during a three-year research project at the *AUTO AG*. Based on observations, the analysis of relevant documents, emails, and a series of discussion interviews, we answer several research questions along the two dimensions of credibility and data and contribute to the understanding of challenges in NPD cost estimation.

As previous scholars pointed out, credibility is a cornerstone for the beneficial application of a cost estimation method (Prince 2002; Smith and Mason 1997). However, the aspect of credibility has not been subject to detailed empirical investigations in the context of NPD cost estimation. We contribute to this gap, by providing several contributions.

First, we suggest that active change management is crucial for a method's credibility when implemented in an organization. Aspects such as proper communication, careful adjustments to the company's specific needs, as well as a long-term sustainability orientation are repeatedly named as important factors for successful change management (Burnes and Jackson 2011; By 2005; Gill 2002). Our study provides empirical evidence that such activities are of special importance in the dynamic and uncertain environment of NPD cost estimation.

Second, we empirically confirm the combination of regression and parametric models as a good fit for NPD cost estimation. Previous authors have presented such approaches but without detailed focus on the factors that make this combination especially fit for NPD cost estimation (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). We show that this concept delivers explainable results, as a method's outcome is clearly connected to premises, but also includes previous data in a statistically significant manner. This makes it superior to potentially more accurate methods, such as the use of artificial intelligence, which might lack explainability (Cavalieri et al. 2004; Loyer et al. 2016; Verlinden et al. 2008). This explainability is desperately needed in NPD cost estimation.

Our third and fourth contributions concern the credibility of the specific *NPD cost benchmarking method*. We find that the method is best used as a tool for the strategic planning of a development portfolio, while it lacks credibility in short-term estimations. This makes it an ideal addition to a company's toolset for strategic planning processes, where methods must be fit to consider a high level of uncertainty (Fairholm and Card 2009; Feurer and Chaharbaghi 1995; Peter and Jarratt 2015).

The fourth contribution of this case study lies in the unveiling of the estimation of modular components as a major weak point of the method. Such components are highly relevant for many industries (ElMaraghy et al. 2013; Jose and Tollenaere 2005; Ramdas et al. 2003), and their cost management is especially challenging (Marion and Meyer 2018; Skirde et al. 2016; Stadtherr and Wouters 2021). Based on the results of our study, we suggest additional, more refined methods to estimate the NPD costs of modular components instead of solely building on the *NPD cost benchmarking method*.

Data plays a critical role in NPD cost estimation, as any kind of method relies on some kind of data. In most NPD cost estimation methods, that data is extracted from internal cost information from an organization's previous products (e.g. Bashir et al. 2006; Bashir and Thomson 2004; Chwastyk and Kołosowski 2014; Gebhardt 2017; Large et al. 1976). Few studies also incorporate external data, but without empirically investigating the challenges of using such data for NPD cost estimation in actual organizations (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). Several of our study's contributions give relevant insights on the aspect of data in the context of NPD cost estimation.

The fifth contribution of this study unveils the comparability problem as the main challenge when estimating NPD costs based on external data. Although the *NPD cost benchmarking method* is a functional example of an approach building on external data, we see typical comparability problems of inter-company benchmarking activities (Bhutta and Huq 1999; Markin 1992; Shetty 1993) especially critical in the context of NPD cost estimation. We conclude that such approaches must always incorporate adjustment steps that increase data comparability. However, we want to raise awareness, that full comparability will most likely never be achieved, due to the character of activities in NPD.

The sixth contribution of this study unveils that the poor-quality data usually available for NPD cost estimation is not as critical as often assumed (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015). We find that stakeholders in this area are familiar with those challenges regarding the availability of comparable data, which is why companies find ways to manage the issue also by accepting it as given. In this context, we confirm insights from the knowledge management and philosophy literature, where acceptance of uncertainty is considered a natural part of life, and humans tend to accept certain uncertainties in their specific environment as given (Douglas 2001; Li et al. 2013).

As the seventh contribution of this study, we empirically show that poor-quality data in NPD cost estimation can sufficiently be replaced by expert knowledge. Previous scholars have shown that such tacit knowledge is crucial for a company to learn as an organization (Barão et al. 2017; Dixon 2017; Saadat and Saadat 2016). Our study emphasizes the importance of such activities in the context of NPD cost management.

As any scientific work, this study has several limitations. First, we could only observe the implementation and application of a single NPD cost estimation method at one specific company. To improve our understanding of the specific method and NPD cost estimation methods in general, observations in other organizational environments would be enlightening. Second, despite conducting a three-year research project, the judgement regarding challenges in NPD cost estimation could be improved by investigating on a longer basis, especially as the long, uncertain, and complex process of NPD can easily take several years until completion (Deng and Yeh 2010; Johnson and Kirchain 2011; Liu et al. 2013; Mileham et al. 1993; Stewart et al. 1995; Tyagi et al. 2015; Wu et al. 2015).

The results of our study provide several promising aspects relevant for future research. First, we want to motivate scholars to build on our insights in the development of novel NPD cost estimation techniques. The challenges we unveil in this study are not yet fully incorporated in the scarce body of existing approaches (e.g. Adelberger and Haft-Zboril 2015; Heller et al. 2012; Lambert and Sackett 1959; Tu and Xie 2003) for this challenge and should therefore be considered for practical validity of future methods. Second, we suggest that scholars further investigate the role of change management in the introduction process of new cost estimation methods. We could see that such activities improve the credibility of NPD cost estimation methods, similar to the generally positive impact of such activities (Burnes and Jackson 2011; By 2005; Gill 2002). Therefore, we want to motivate scholars to look for further improvement potential and investigations on this aspect in general. Third, we see room for appealing research projects on organizational knowledge management in the context of NPD cost estimation. Our study shows that expert knowledge plays a crucial role in NPD cost estimation, as it can replace poor-quality data. We suggest finding ways to improve organizational knowledge management practices (Barão et al. 2017; Dixon 2017; Saadat and Saadat 2016) to build NPD cost estimations on a more solid foundation regarding usable data.

5 Heuristics for managing NPD projects: Conceptualization and empirical test of a within-project NPD cost compensation heuristic

Abstract

Decision-makers often use heuristics for managing new product development (hereinafter NPD) projects. Unexpected events during the project require making new decisions about product performance, development lead time, and development costs. Heuristics are decision rules that, instead of aiming to optimize in situations where data and models are anyway far from perfect, provide reasonably good decisions on the basis of fewer data and less extensive but faster decision-making processes. First, this study conceptualizes a novel heuristic for managing NPD projects, which prioritizes the goal to keep NPD costs in check by requiring teams to compensate NPD cost overruns elsewhere within their project. Second, the study empirically investigates factors associated with the use of this *within-project NPD cost compensation heuristic* (hereinafter also *compensation heuristic*). These factors are based on the need and the feasibility to find compensation. Third, this study provides a further understanding of ongoing budget allocation decisions at the NPD project-level.

Keywords: *new product development projects; new product development costs; uncertainty; heuristics*

5.1 Introduction

New product development (NPD) is often a crucial but uncertain and expensive endeavor. It is essential for the long-term success of many companies (Artz et al. 2010; Brown and Eisenhardt 1995; Chao and Kavadias 2008; Hauser et al. 2006; Talay et al. 2014), but the costs for developing new products can be substantial (Artz et al. 2010; Cooper and Kleinschmidt 1996; Cooper and Slagmulder 1999; D'Este et al. 2012). Decisions about product performance, development time, and development costs set the stage for the new product's future profitability, but decision-relevant information is often limited or unreliable. NPD activities are future-oriented, and many things are difficult to predict, leading to technological uncertainty (for example, regarding NPD lead time, NPD costs, or unit manufacturing cost) and commercial uncertainty (for example, regarding success in the market, profit margins, and sales volume) (Davila 2000; Laine et al. 2016; Lasso et al. 2020; Santiago and Bifano 2005; Sicotte and Bourgault 2008; Tatikonda and Rosenthal 2000; Um and Kim 2018).

Prior research has investigated various approaches for managerial responses to uncertainty, including the real options approach: spreading and limiting risks by investing in a wide range of early-stage, promising projects, and later discontinuing some of these projects on the basis of new, unfavorable information (Kaufmann et al. 2021; Klingebiel and Rammer 2014). The most "extreme" form of that approach is taken by venture capitalists investing in innovative new ventures, which is sometimes adopted by corporate venture units (Hill et al. 2009). However, project abandonment in a corporate setting is very difficult to actually do (Adner and Levinthal 2004) and research has investigated various factors influencing project abandonment (Kaufmann et al. 2021; Klingebiel and Adner 2015; Long et al. 2020; Subramanian and van de Vrande 2019; Vaculik et al. 2019).

Studies have also investigated subtler responses than complete project abandonment when new information becomes available during NPD projects and decisions must be taken. These responses involve that teams reconsider some of their initial decisions on product performance, development lead time, and development costs (van Oorschot et al. 2011). However, the adjustments in terms of product performance, development time, and development costs are not necessarily based on full-fletched analyses of all financial implications, but on efficient shortcuts. In principle, the adjustment decisions could every time call into question “all” decisions and try to capture “all trade-offs” between product performance, development time, and development costs. For example, when technical difficulties require unforeseen, additional, and substantial engineering work, the team could evaluate to what extent the optimal response involves allowing extra development lead time or cancelling particular other engineering tasks - these responses could impact the moment of market introduction, the product performance, sales prices, and total units sold - or spending extra resources on product development to avoid delays and product compromises. Yet, quantifying these trade-offs among time, costs and performance is time-consuming and extremely difficult to do (Langerak et al. 2008; Langerak et al. 2010; van Oorschot et al. 2011). The required data is lacking or unreliable, and the relationships between these various consequences can only be incompletely modeled.

In the complex and uncertain NPD environment, teams often have to use simpler decision heuristics that use less information, are faster, introduce inaccuracies, but which may still work better than decision strategies that are more complex and require more information (van Oorschot et al. 2011). Heuristics in these studies are not understood as biases and other mistakes and limitations that play a role in human judgement and decision-making processes (Stingl and Geraldi 2021). Rather, these heuristics are decision rules that, instead of aiming to optimize in situations where data and models are anyway far from perfect, aim to provide reasonably good decisions on the basis of less data and less extensive but faster decision-making processes (Bingham and Eisenhardt 2011). The focus is on satisficing decision rules in the face of uncertain, complex projects (Eriksson and Kadefors 2017).

We build on these ideas to develop and empirically investigate a novel heuristic, which we term the *within-project NPD cost compensation heuristic*. The decision context matters greatly for understanding the use of heuristics in management (Stingl and Geraldi 2017) and we consider NPD projects during which unexpected events occur that require new, additional NPD efforts. For example, technical problems arise for developing the new product or the required production processes for it, legislation or technical standards change, new market information reveals that customers strongly prefer a change of product performance, or a competitor announces they will introduce their product sooner than expected. The team requires additional budget for undertaking the new, additional NPD efforts. However, the additional budget threatens to make the NPD project more expensive. The *compensation heuristic* means that teams do not get additional budget but need to focus on staying within the NPD project budget by cutting NPD costs elsewhere in the project. In other words: they need to try and find compensation for the overspent.

We investigate several factors that would be associated with the use of the *within-project NPD cost compensation heuristic*. We test our predictions based on a proprietary data set of an automotive company. The data pertain to nine large projects for developing a new vehicle model, leading to 526 NPD budget allocation decisions for this set of projects that are included in the study. The average NPD budget for one project was around 930 million Euro and these projects had a lead time between four and nine years. Most of the budget allocation decisions (95%) varied between -8 million Euro and +35 million Euro. The automotive company provided a very suitable research site because NPD is crucial in this industry, NPD projects are often very large and expensive, and uncertainly plays a key role during NPD projects (Chauhan et al. 2020; Martinez Sanchez and Perez Perez 2003; Talay et al. 2014; Townsend and Calantone 2014). Long NPD project lead times in automotive, for example, make it difficult to predict external future developments such as technological developments, material and part costs, customer preferences, and competitor actions (Ili et al. 2010; Munthe et al. 2014).

This study provides several contributions to the literature. First, we add to the literature on managing uncertain NPD projects by conceptualizing the *within-project NPD cost compensation heuristic*. Research demonstrated that NPD project teams use various heuristics to guide their decision-making during complex and uncertain NPD projects (Sarangee et al. 2014; van Oorschot et al. 2010). These heuristics consider one dominant objective when making decisions during NPD projects that are going differently than initially planned. For example, a heuristic could be to prioritize NPD lead time and therefore remove troublesome product features or increase NPD resources, or the heuristic could prioritize product performance and improve this to compensate for late product introduction or higher prices. These heuristic decision rules do not try to optimize trade-offs between product performance, development time, and costs, but prioritize one objective for decision-making in response to new information. Our study adds to this literature by introducing the *within-project NPD cost compensation heuristic*, which prioritizes keeping NPD project costs in check.

Second, besides providing a new conceptualization of the *compensation heuristic*, this study offers empirical support for factors that are associated with its application. The overall idea is that NPD project cost compensation is larger, as there is a *greater need* to compensate NPD costs and *more possibilities* exist for finding compensation. We find support for the hypotheses that within-project NPD cost compensation is positively related to the level of frontloading and negatively related to financial project performance, availability of resources, sunk costs, and level of innovation. Some of these factors have been shown to play a role for managing uncertain NPD projects, in particular as factors that may influence the actual abandonment of projects based on new, negative information (Andries and Hünermund 2020; Chao and Kavadias 2008; Huchzermeier and Loch 2001; Loch and Kavadias 2002; Manez and Love 2020). We add to this literature by showing that these factors are conducive to the application of the *compensation heuristic*, as another approach for responding to unfavorable news about ongoing NPD projects. We also add to the literature that has investigated factors that are associated with the use of heuristics (Gupta et al. 1992; Vepsalainen and Lauro 1988). In particular, our variables financial project performance (Calantone et al. 1999; Venkatraman and Venkatraman 1995) and resource availability (van Roy and Gelders 1978) were identified as drivers of simplified or heuristic decision-making.

As the third contribution, we add to the literature on budget allocation decisions for NPD projects. Some studies consider budget allocation as an ongoing decision-making process at the NPD project-level. This literature comprises models for a financially optimal funding path, considering unexpected project-level events (Kester et al. 2011; Lint and Pennings 2001; Loch and Kavadias 2002; Messica and David 2000; Repenning 2001). However, empirical insights are mostly missing about how such decisions in an ongoing NPD project budgeting environment are made. We contribute to this literature by providing a complementary understanding of ongoing budget allocation decisions as a way for responding to unexpected events, which threaten to increase the NPD project cost. Our study suggests that a company may take subsequent budget allocation decisions to try and compensate for such cost overruns and limit the increase of the NPD project cost.

The remainder of this study is structured as follows: We start giving an overview of the relevant literature before we motivate and introduce the concept of the *compensation heuristic*. Afterwards, we present our empirical study and conclude with a discussion of this work's contributions to the literature, its limitations, and an outlook on future research opportunities.

5.2 Theoretical framework and hypothesis development

5.2.1 Real options NPD project management

The real options approach focusing on project abandonment is a common method to manage a project portfolio in NPD (Kaufmann et al. 2021; Klingebiel and Adner 2015; Newton et al. 2004). Decision-makers in NPD repeatedly face technical and commercial uncertainty (Davila 2000; Tatikonda and

Rosenthal 2000). Such uncertainties (for example, regarding lead time, profit margins, or sales volume) cannot be resolved completely and therefore must be considered in managerial decision-making (Atkinson et al. 2006; Santiago and Bifano 2005; Um and Kim 2018). One way to manage such uncertainties in project management is the real options approach: to spread risks across the product portfolio, decision-makers invest in a wide range of promising early-stage projects. At a later stage, as new information arises, these projects are re-evaluated and some of them are discontinued. Newton et al. give a comprehensive overview about the use of such real options in research and development (Newton et al. 2004). The studies of Kaufmann et al. (2021), as well as Klingebiel and Rammer (2014), attest, that a real options approach can be beneficial for the performance of a firm's product portfolio development strategy. Huchzermeier and Loch (2001) introduce the option of corrective action as an addition to the familiar real option of abandonment.

In the venture capital investment industry, decision-makers heavily apply the real options logic: by investing in a wide range of promising early-phase ventures, investors spread their risk of failure. Through re-evaluation later on, new information is considered and ventures that do not seem promising anymore, are denied further funding (Guler 2015; Li and Chi 2013). Hill et al. (2009) empirically analyze the transferability of the venture capital model to the corporate context, attesting a higher unit performance from staged investments which are typical in the venture capital industry.

Such a strategy based on project abandonment is often difficult to pursue in a corporate setting. Adner and Levinthal (2004) investigate boundaries for the application of real options theory for business strategy and argue that it can result in a trade-off that "may lead to the underutilization of discoveries made in the course of exploration". Several authors propose that the character of NPD denies a radical project abandonment strategy as proposed by the classical real options logic. Long et al. (2020) argue in their experimental study, that project abandonment in NPD tends to be delayed and also depends on the stage of development: while chances of project abandonment are higher near the middle, the decision to terminate a project at the beginning or towards its end is less frequent. Subramanian and van de Vrande (2019) investigate the role of intellectual capital as an influence factor on NPD decision-making: projects that have a high level in all three dimensions of intellectual capital (human, structural and social capital) are less likely to be discontinued. They also emphasize the mitigating influence of the portfolio-size as well as the enhancing impact of discontinuation experience on the relationship between intellectual capital and the decisions to terminate projects in NPD. Vaculik et al. (2019) empirically show that the termination of innovation projects is positively influenced by various factors, such as firm size, the level of internationalization, or marketing innovation. As a consequence of such lacking project-termination, decision-makers in NPD tend to escalate their commitments, although projects do not promise a positive outcome (Liang et al. 2014; Schmidt and Calantone 2002).

5.2.2 Ongoing budget allocation decision-making

A systematic overview of quantitative techniques, trends, and representative examples for R&D project selection and resource allocation is given by Heidenberger and Stummer (1999). While they conclude that R&D resource allocation heavily depends on the decision-makers in a given situation, they also emphasize the importance to supplement quantitative techniques with "soft" approaches, like the involvement of experts. Blanning (1981) proposes variable-based budgeting for R&D. He develops three models for the proper allocation of resources to a company's development portfolio. The extremes of incremental budgeting (mostly based on previous allocations) and zero-based budgeting (ignores previous allocations) are compared, and the concept of variable-based budgeting as a middle way is presented. The author concludes that a policy of zero-based budgeting is not optimal for application in all stages but might be beneficial for some cases. Loch and Kavadias (2002) argue that the allocation of resources to product lines is not an all-or-nothing decision but is subject to adjustments by the decision-makers. In their model based on marginal returns, they propose that even on the level of individual projects, the overall budgets or the budget for a specific period can be altered between periods. Ayal and Rothberg (1986, p.238) emphasize the problem by analyzing the control systems companies apply. They propose a distinction between effectiveness and efficiency of R&D spending and conclude that most companies "overcontrol such allocations in terms of tactical detail or efficiency consideration, and undercontrol in terms of strategic significance or effectiveness." Their work gives insights about an appropriate design of R&D resource allocation systems as part of managerial control in organizations. Chao and Kavadias (2008) present a way of balancing incremental and radical innovation through strategic budgeting buckets. These buckets allow managers to steer the innovation process with more precision and less complexity. Based on this theory, they find effects on the balance between incremental and radical innovation through simulation: if the external complexity is high, more incremental innovation is pursued through strategic buckets. Santiago and Soares (2020) also take on the idea of strategic buckets as they pursue a case study based on seven multinational companies from different industries. Their framework is based on four strategic constructs: technology, market, capabilities, and organizational processes. They discuss how these constructs react to external influence factors and describe how they can be combined.

Although the allocation of resources across multiple projects in an NPD project portfolio is crucial for efficient resource management, we focus our work on another, more nuanced way in which companies make R&D resource allocation decisions in practice: sequential budget allocation decisions for a single NPD project. Due to the high level of uncertainty in NPD, resources are usually not allocated to projects all at once, but rather dynamically. With these sequential funding decisions, teams react to unexpected project-level events (Deshmukh and Chikte 1977).

Several authors present approaches to the definition of optimal paths for the sequential spending of resources for R&D projects. Hess (1962) approaches the R&D budgeting problem by utilizing dynamic programming to determine optimal spending for environments of constrained and unconstrained budgets. Lucas (1971) differentiates between situations in which the completion time of a project is either known or unknown. He also considers whether the cost per unit of time is fixed or variable. Similar, Kamien and Schwartz (1971) consider the total effort for the completion of a project as unknown for their model. Aldrich and Schwartz (1975) put attention on the returns of an NPD problem and how it affects the optimal spending course. By modelling the possibility of time-dependent returns, they define the optimal spending rate as a function of the effort already invested. Deshmukh and Chikte (1977) propose that the status of a development project changes stochastically, which makes it crucial to reconsider fundings for a project in regular terms. Their model, which includes various types of uncertainties, allows giving an evaluation at any point during the project on whether and how to continue funding an NPD project as well as when it is time to discontinue the said project. Roberts and Weitzmann (1981) uncover three dependencies that are relevant when funding a sequential project: first, the optimal plan depends on whether all stages of the project need to be completed for the generation of benefits; second, the funding plan is affected by how much the arrival of new information during a stage influences the development plan; third, it is relevant whether running costs that are remaining after cancelling a project fall slower or faster than the terminal benefits. Mehrez (1983) also investigates the role of changing returns on the optimal spending plan by pursuing a sensitivity analysis based on previous models. Additionally, he redefines the measurement of marketing uncertainty to increase the relevance of his model to practical decision-making in NPD. The incorporation of uncertainties is also subject to the work of Zuckerman (1980). To model the uncertainty within NPD projects, he models the project status changing during the development time following a diffusion process. Kamien and Schwartz (1974) explicitly include technical and marketing uncertainty into their approach for an optimal spending plan. The model of Granot and Zuckermann (1991) expands the concept of processes in NPD as they maximize a project's net present value through the sequential selection of specific development activities. According to Dutta (1997), the timing of profits within an NPD project is crucial for the optimal allocation of budgets between stages of NPD. He proposes that the ideal strategy is to divide the budget evenly among all stages if the profit only occurs after all stages are successful. Messica et al. (2000) expand the discussion by introducing a double-path engineering project as the object of analysis. They describe such a project as one with a risky as well as a nonrisky path and investigate the interplay between them and their effect on the optimal spending behavior. A mathematically new way of solving the optimal sequential

R&D allocation problem is brought forward by Messica and David (2000): Building on the theory of differential equations, they find a new and superior solution for the problem. Huchzermeier and Loch (Huchzermeier and Loch 2001) do not only investigate the influence of the timing of resolved uncertainties of various kinds on the value of managerial flexibility options but also expand the real options approach in sequential R&D resource allocation with the approach of corrective action. Lint and Pennings (2001) propose a two times two matrix that compares uncertainty with R&D real option value to decide whether to speed up or delay an NPD project. Depending on the position of a project on this matrix, which they developed based on insights from the development process at Philips electronics, dynamic portfolio decision-making can be supported. Repenning (2001) describes the concept of fire fighting as the process in which companies have to allocate resources during a project to cover unexpected developments. The author concludes that the phenomenon is self-reinforcing and further suggests that it is widely underappreciated in the existing guidelines for the successful management of a development portfolio. Kester et al. (2011, p.641) emphasize that development portfolio decision-making must be understood as an “integrated system of processes”. Based on insights from four diverse case studies, they set up a framework presenting guidelines for efficient and dynamic decision-making in this context.

Although a range of studies contributes to our understanding of ongoing budget decision-making, they almost exclusively take the viewpoint of finding an optimal path. What the literature currently lacks, are empirical insights on the way single decisions are made in the context of ongoing NPD project budgeting.

5.2.3 Decision-making heuristics for managing NPD projects

Heuristics are decision rules that do not aim to optimize based on much information and complex decision algorithms, but instead use less information and simple, fast decision rules. Although they introduce inaccuracies, heuristics may still work better in complex, dynamic decision contexts, where the availability and reliability of data, as well as the validity of models, are very limited (Stingl and Geraldi 2021). New ventures (Åstebro and Elhedhli 2006; Bingham and Eisenhardt 2011) and large infrastructure projects (Eriksson and Kadefors 2017), for example, are the contexts in which the use of heuristics has been studied.

The character of NPD with its high complexity and unexpected events during projects makes it predestined for the application of simplified decision-making processes such as heuristics in management (Langerak et al. 2010; Stingl and Geraldi 2017; van Oorschot et al. 2011). Managing NPD projects involves the challenge of responding to uncertainty when data and decision models are far from perfect. It is often not feasible to determine the optimal interventions when new information becomes available about, for example, customer preferences in the market, technological difficulties in NPD, or material cost increases. The interdependencies between development costs, sales volume, cycle time, proficiency in market-entry timing, and new product profitability are often too complex, or too unpredictable (Langerak et al. 2008). Therefore, decision-makers often rely on mental models for decision-making that do not consider trade-offs but always prioritize one particular goal when making decisions. For example, product development time influences product development costs as well as new product sales in complex ways. But instead of considering both effects to maximize new product profitability, teams often use mental models that focus only on either development costs or new product sales (Langerak et al. 2010).

Because of the complex and uncertain environment of organizational NPD, heuristics play an important role in managing NPD projects. Van Oorschot, Langerak, and Sengupta (2011) investigate heuristics for reacting when NPD projects are running behind schedule, using simulation of system dynamics. Their three distinct heuristics prioritize either development time, development cost, or product performance. According to the time heuristic, teams focus on development time and increase the team size to speed up delayed projects. Using the cost heuristic, teams focus on development costs and accelerate delayed projects by reducing product performance. The performance heuristic means that teams do not speed up delayed projects, but increase product performance to compensate for late product introduction. These heuristics are compared to the do-nothing heuristic, which means that "development teams are unlikely to intervene at all in projects that run behind schedule, in the hope that the project will succeed anyway" (page 849). Results show that all three decision heuristics are superior to doing nothing, but combining heuristics is the most effective approach. A combination of development time and product performance heuristic is beneficial if schedule issues are uncovered early in the project, while a combination of development time and development cost heuristic is the best intervention if problems arise late in the project.

Several other studies also show that intuition and heuristics play an important role for selecting NPD projects and allocating resources. Petrick and Echols (2004) investigate a firm's decision whether or not to develop a new product. Instead of traditional financial decision-making methods such as net present value, they propose that companies should adopt a broader heuristic for making new product development decisions. The essential criterion would be how a new product builds on the firm's technological resources, which it develops to fit expected long-term technological trajectories in society (i.e., technology roadmaps) and developments in customer markets. Sukhov et al. (2021) investigate heuristics when decision-makers select which product ideas to pursue for development. Decision-makers often apply rapid, intuitive judgments of idea quality, but how they think while screening is largely unknown. The authors use the think-aloud method to investigate how experts identify high-quality ideas. They find that the experts' thinking processes can be broken down into seven key activities to identify high-quality ideas in the short-term and/or long-term. Tavares, Santiago, and Vakili investigate the impact of heuristics that managers use for NPD project selection. In their model, the optimal R&D portfolio selection depends on the complex trade-offs between the probability of development success of projects, which can be influenced through the allocation of the development budget to projects, the stochastic return of projects in the market, and the company's risk aversion. Using heuristics, managers focus on particular aspects of the problem. One heuristic selects the R&D portfolio by focusing on the maximum commercial returns of the projects. Another heuristic focusses on minimizing commercialization risks, and a third heuristic on maximizing development success. Depending on the heuristics that managers follow, the number and type of projects that they select for development varies. West, Acar, and Caruana (2020) draw on cognitive psychology to find out how marketing managers make initial product screening decisions to invest in an idea. They build on data from 122 senior managers to identify five main decision-maker profiles in terms of the mix of instinct, heuristics, and analytics in decision-making. They also link these decision-making types with the accuracy and speed of decisions. They find that with the help of heuristics that are used alone, or in combination with intuition, managers make decisions that are comparably accurate as solely relying on analytical decision-making. However, the process is significantly faster.

5.2.4 The within-project NPD cost compensation heuristic

This study adds to our understanding of heuristics for managing NPD projects by introducing an additional heuristic. The *within-project NPD cost compensation heuristic* prioritizes keeping NPD costs in check when these threaten to increase, for example, if technical problems arise during development, market demands change drastically, or new information reveals that competitors will introduce their product sooner than expected (Davila 2000; Laine et al. 2016; Lasso et al. 2020; Santiago and Bifano 2005; Sicotte and Bourgault 2008; Tatikonda and Rosenthal 2000; Um and Kim 2018). The development team requests additional resources for activities to react on these unexpected events.[25] A decision must be made on how to fund the project's activities. The *compensation heuristic* focusses on NPD costs and makes the development team focus on staying within the NPD project development budget by reducing NPD costs elsewhere within

[25] In principle, unexpected events could also make fewer NPD efforts necessary, and teams could return some of their budget, instead of requesting additional funds. We do not exclude this from our conceptualization of the *compensation heuristic,* but we focus on the more challenging setting of budget increases.

the project. In other words: they try to stick to the so-far allocated resources and find compensations for the required resources.

The *within-project NPD cost compensation heuristic* is somewhat comparable to the cost heuristic of Van Oorschot, Langerak, and Sengupta (2011) mentioned earlier, as both focus on development costs. The *compensation heuristic* has also some resemblance to the feature-level de-escalation heuristic identified by Sarangee et al. (2014), which also focuses on NPD costs. That study investigated organizations operating in high-technology environments. Based on qualitative data from 31 managers and engineers covering 15 NPD discontinued projects, the study identifies several new de-escalation mechanisms that help decision-makers to abandon NPD projects that are in trouble, and to redirect resources to more promising projects. However, the study also identifies the feature-level de-escalation heuristic that does not involve termination but "removing individual features of a product that are especially troublesome, even major ones, and thereby not cancelling the entire project" (p. 1032). However, the *within-project NPD cost compensation heuristic* is specifically different from these in that the product requirements are not adjusted. This aspect of the *compensation heuristic* is based on the idea that in the uncertain NPD project environment, other unexpected events may reduce some of the required resources for the project. For example, some technical solutions may turn out to be easier and less costly to develop. To some extent, within-project NPD cost compensation may be possible by drawing on such favorable differences to fund additional resource requirements due to unfavorable differences.

According to the *within-project NPD cost compensation heuristic*, decision-making about the budget for an NPD project is an ongoing process. Allocating a budget to an NPD project refers to the decision that a particular amount of resources, expressed in a monetary unit of measurement such as Euro or Dollar, is assigned to be used for a particular project. The optimal allocation of an overall NPD budget to NPD projects is an important topic in the literature. Many models focus on the optimal allocation of an overall NPD budget to multiple projects in a particular portfolio (and for a particular time horizon). Although some of these studies incorporate dynamic aspects of budget allocation, most of them consider the allocation as a one-time, initial decision for each NPD project (Ayal and Rothberg 1986; Chao and Kavadias 2008; Heidenberger and Stummer 1999; Liberatore 1987; Santiago and Soares 2020). Other research considers that uncertainty at the NPD project-level may require multiple decisions for each project to adjust the budget allocation. Those models focus on optimal funding paths for sequential budget allocation decisions to NPD projects (Kester et al. 2011; Lint and Pennings 2001; Loch and Kavadias 2002; Messica and David 2000; Repenning 2001). Although a range of studies contributes to our understanding of ongoing NPD budget decision-making, these are almost exclusively from the viewpoint of finding an optimal path. What the literature currently lacks, are empirical insights on the way single decisions are made in the context of ongoing NPD project budgeting. The *compensation heuristic* also considers multiple budget allocation decisions for each NPD project and our study aims to provide a better understanding of how such decisions are made in particular contexts.

5.2.5 Hypotheses development

We do not only present the *compensation heuristic* as new conceptualization, but we also offer empirical support for factors that are associated with its application. The overall idea is that within-project NPD cost compensation is done to a greater extent as there is a greater need to compensate NPD costs and more possibilities exist for finding NPD cost compensation within the scope of the same project. Based on this, we introduce several hypotheses.

The need to compensate NPD costs within the same project is investigated with the variables level of frontloading, financial project performance, and resources available. *Level of frontloading* refers to the extent to which more or less resources have already been allocated to an NPD project than originally planned at a specific point in time. A greater level of frontloading means that the amount of allocated resources is further away from what would be expected given the degree of completion of the NPD project.

If unexpected events appear to require yet additional resources, the amount of allocated resources would move away even further from what would be expected. The pressure to not allocate additional resources but to compensate NPD costs is likely greater, the more the allocated resources are already inflated. Thus, we expect a larger need to compensate in situations in which the level of frontloading is high.

> **Hypothesis 1:** Within-project NPD cost compensation is positively related to the current level of frontloading.

Financial project performance in this study refers to the forecasted lifecycle profitability of the product that is being developed during the NPD project. In other words: the financial soundness of the business case for developing and launching the new product. The better shape the expected profitability of the new product is in, the more additional NPD costs are affordable and the fewer NPD cost compensation possibilities the team needs to find. So, we expect a smaller need to compensate in situations in which the financial project performance is high.

> **Hypothesis 2:** Within-project NPD cost compensation is negatively related to current financial project performance.

Resources availability in this study refers to the level of financial means that are at the disposal of the organization conducting the NPD project. The more resources are available in the company, the less likely the team might be under pressure to look for cost compensation within the project and they might rather try to obtain additional resources and will more likely be successful at that. Thus, we expect a smaller need to compensate in situations in which more resources are available.

> **Hypothesis 3:** Within-project NPD cost compensation is negatively related to current resources availability.

The possibility to compensate NPD costs within the same project is investigated through the variables sunk costs and level of innovation.

Sunk cost in this study refer to the amount of resources already allocated to an NPD project. As the NPD project progresses and more resources have been allocated, fewer degrees of freedom remain for compensation. Fewer NPD activities remain, so there are simply fewer activities left that could potentially be altered for cutting NPD costs. Moreover, as more aspects of the product have become fixed as the NPD project progressed, the possibilities for changing those remaining NPD activities are also more limited than they would have been the case earlier into the project. For those two reasons, it is probably less possible to find within-project NPD cost compensation as the project has progressed more and sunk costs are larger.

> **Hypothesis 4:** Within-project NPD cost compensation is negatively related to sunk costs.

Level of innovation in this study refers to the extent to which the new project is novel in terms of product or production technology. As the level of innovation increases, a project becomes more demanding - it is more difficult to develop the novel product or production technology. More technological challenges must be solved. Other dimensions of the NPD project than NPD costs take more time and attention, have a greater priority, and create more constraints. The possibilities to find NPD cost compensation within the projects are scarcer, so we expect a smaller possibility to compensate in situations in which the level of innovation is high.

> **Hypothesis 5:** Within-project NPD cost compensation is negatively related to level of innovation.

In sum, managing NPD projects is a cornerstone for innovative companies. In the previous chapters, we saw that decision-making in this uncertain environment, especially in the context of budget allocation, is complex and challenging. We also saw that a classical real options approach based on project abandonment is not always feasible for NPD portfolios, as teams react to unexpected events in a more nuanced way. With this work, we want to shed light on these decision-making processes by investigating ongoing budget allocation decision-making. To face unexpected events, teams must decide whether they allocate additional resources or compensate the additional needs through available means. As the complexity of these decisions does often not allow an analytically optimal model, we propose that decision-makers follow a *compensation heuristic*. This *within-project NPD cost compensation heuristic* helps to understand ongoing budget allocation decision-making as a reaction to unexpected events in the uncertain environment of NPD project management.

5.3 Research Method

5.3.1 Data on budget allocations for NPD projects

To investigate the *within-project NPD cost compensation heuristic* and test our hypotheses, we use proprietary archival data about NPD projects of an automotive company. We interacted with many people in the finance department of new product development to understand how NPD projects were being managed, processes for allocating budgets, and the meaning of the quantitative data.

Resources were assigned to NPD projects by a management committee, constrained by the overall NPD budget. Due to the high level of uncertainty, the resources that a development project required for completion were not allocated through a single decision, but sequentially throughout the project. Two types of resource allocation decisions could be differentiated: planned allocations and unplanned allocations. Planned allocations were made at specific milestones during the project and represent major shares of the overall planned NPD costs. These allocations did not resemble a direct reaction to unexpected events during the projects but were triggered by the project processing through the development stages. The second kind of decisions, and the focus for this work, are allocation decisions as a direct reaction to unexpected events. Various occasions could trigger these decisions, such as technical problems with certain parts or changes in market demands. In these cases, specific unplanned allocations were made to put additional effort into developing suitable solutions.

The data for this study concern nine NPD projects. The company's NPD resource allocation database included all NPD resource allocation decisions made from 2010 until 2020, and for each of these decisions, several attributes were listed, such as the corresponding vehicle development project, the amount allocated, and the decision date. To cover projects through their entire life cycle, we focus on development projects that were in the database from their beginning until the start of production, yielding nine such complete projects.

Planned resource allocation decisions were triggered by milestones and are larger amounts. Therefore, to focus on unplanned resource allocation decisions that were a reaction to unexpected events, allocations of up to 5% of the overall NPD budget for the project were included. If multiple resource allocation decisions were made for the same project on the same day, we summed the amounts and included this as one decision per day. In total, the sample includes 526 resource allocation decisions. Table 27 provides an overview. We empirically test our hypotheses with a linear regression model with the *compensation heuristic* as the dependent variable and several factors influencing the use of this heuristic as the independent variables.

Table 27: Descriptive statistics of the sample of NPD-level budget allocation decisions

Project	Project duration (from first to last budget allocation decision) (years)	Project NPD costs at completion (millions of Euro)	Number of NPD budget allocation decisions considered[a]	Largest NPD budget allocation decision considered (millions of Euro)[a]
P1	4.2	297	25	13.5
P2	4.2	304	40	6.0
P3	7.8	736	91	36.0
P4	4.5	607	35	19.6
P5	9.1	2,304	122	85.6
P6	4.4	602	40	19.6
P7	5.2	346	56	15.0
P8	6.0	2,157	59	107.6
P9	7.8	997	58	26.0
Total			**526**	

[a] excluding allocations that account for more than 5% of a project's total NPD costs

5.3.2 Measurement of the within-project NPD cost compensation heuristic

We measure the *within-project NPD cost compensation heuristic* based on changes in the deviation between the planned allocation and the actual allocation throughout a development project. The *compensation heuristic* circles around the question how decision-makers react to unexpected events in terms of resource allocation. When faced with such events, two options are thinkable. First, the company could try to cover that additional resource requirement completely or partially through resources that were already allocated or were going to be allocated to the project. In such a case, no additional resources are allocated to the project and we talk about compensation. The second option is to allocate additional resources to the project in response to unexpected events, which represents no compensation.

To measure the planned allocation of resources to a project, we define the budget-allocation timeline. This is based on the data from the nine vehicle projects. This timeline disaggregates the total budget for a vehicle project and shows how the authorization for spending the budget (i.e., the allocation of budgets) "grows" from 0% to 100% from the first to the last day of the NPD project. First, we measure each day in an NPD project as a percentage of the entire project duration (for example, day 100 of a 1,000 day-long NPD project is measured at 10%). Similar, we measure the percentage of resources allocated until that day as a percentage of the final budget at the end of the project. Second, we cluster the data points to avoid biases through projects of different lengths. We define 100 intervals that each contain 1% of the days within an NPD project (all data points measured between 0% and 1% of the days within an NPD project go into the 0.5%-interval, all data points between 1% and 2% go into the 1.5%-interval, and so on) and calculate the average percentage of the budget allocated to a project across the days within that interval. This leaves us with 900 data points that contain information about the average cumulative budget allocated within each interval across all projects. We estimate a quadratic regression model that represents the relationship between the moment within an NPD project and the percentage of resources that are allocated until this day. The result is used to construct the specific budget-allocation timeline for each project. We use it to assign a percentage of the total budget allocated to each day during a development project. Multiplying the initial target of the project with the percentages yields the absolute value of the budget-allocation timeline for every single day during the project's development cycle.

The budget-allocation timeline shows the ongoing budget allocation to the NPD projects. Comparing the actual R&D resources that were allocated at any point t during the project to the corresponding value of the budget-allocation timeline at the same point t, allows us to evaluate whether project p currently is above or below the spending plan indicated as $\Delta Target_{pt}$. We look at this difference at each NPD budget allocation decision and consider whether it has become larger or smaller towards the next NPD budget allocation decision. If this distance became smaller (i.e., the vehicle project moved back closer to the budget-allocation timeline), the team has compensated some NPD cost overspending. If the distance became larger (i.e., the vehicle project moved away further from the budget-allocation timeline), the team has not compensated NPD cost overspending.

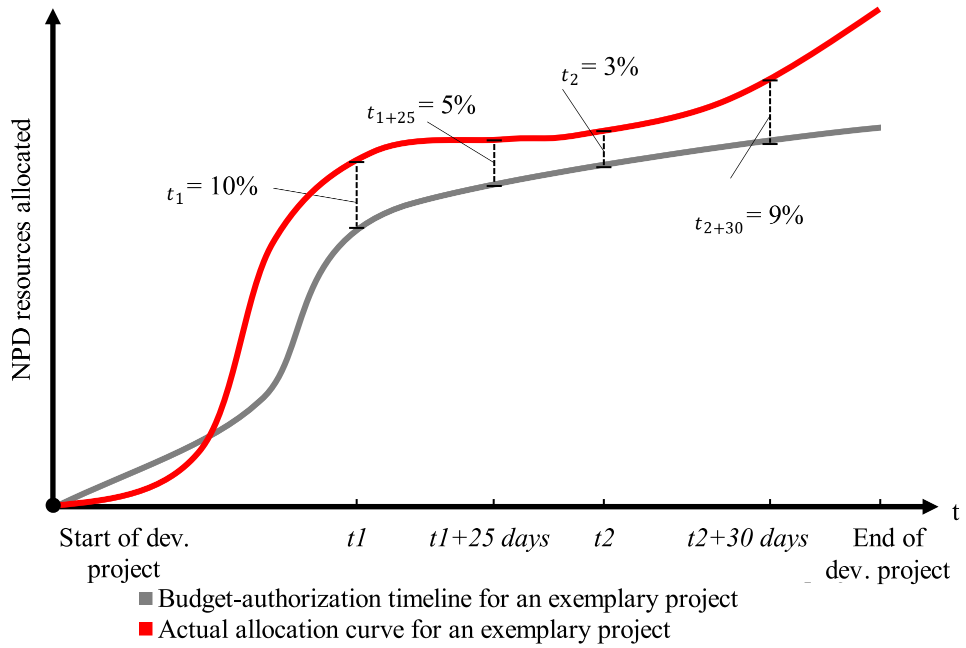

Figure 21: Illustration of the measurement of within-project NPD cost compensation

Figure 21 provides a numerical example to illustrate the measurement. The figure shows the budget-allocation timeline as well as the actual allocation curve for an exemplary project. We measure our concept for two resource allocation decisions made at $t1$ and $t2$. Looking at $t1$, we can see that the red actual resource allocation line is above the grey budget-allocation timeline. This indicates that the company has already allocated more resources to that project at that point in time than they should have according to the original plan. The delta at this moment $\Delta\, Target_{t_1}$is 10%, meaning that we allocated 10% more than we should have until $t1$. The next decision after this point is made 26 days later. Therefore, we measure the delta again at $t1 + 25$ (i.e., the day before the next decision), where it is 5%. This indicates that some of the resources required in $t1$ could be covered by planned allocations leading to compensation. In this case, the corresponding measurement for compensation related to the decision taken at $t1$ would be $\Delta\, Target_{t_1} - \Delta\, Target_{t_{1+25}}$= *10% - 5% = 5%.* We see another pattern for the decision taken at $t2$. The value of $\Delta\, Target_{t_2}$ is 3%, and 30 days later at the day before the next decision, that delta changed to $\Delta\, Target_{t_{2+30}}$= 9%, leading to a measure of $\Delta\, Target_{t_2} - \Delta\, Target_{t_{2+30}}$= *3% - 9% = -6%.* In this case, NPD costs were not compensated within the project, as the additional resources allocated in $t2$ have made the project move further away from the budget-allocation timeline by the time the next time funding is requested.

5.3.3 Measurement of the variables influencing the use of the within-project NPD cost compensation heuristic

Level of frontloading is measured as the relative difference between the budget-allocation timeline and the actual amount of resources allocated to a project p at that point t (= $\Delta Target_{pt}$). Several studies incorporate measurements for similar concepts in the context of NPD budgeting, putting focus on the timely distribution of NPD activities through product phases. Huchzermeier and Loch (2001) evaluate flexibility in the context of different uncertainties in R&D. They measure the concept of frontloading as the overspending during the project compared to the budget. They differentiate two cases in which a project overspent is or is not correlated to an overspent in future periods. Van Oorschot et al. (2010) investigate different strategies on how to react to issues during development projects that are managed following a Stage-Gate approach. They consider a scenario in which the exceeding of a budget is allowed at a certain point during the project and a scenario in which it is not. They measure the level of frontloading in this scenario as the additionally required relaxation of the budget to pursue the overspent.

Financial project performance is measured based on the estimated return on sales of a vehicle project, which was updated every three or four months. To account for project-specific requirements regarding return on sales, we calculate this measurement as the relative deviation between estimated return on sales at t and the initial target for return on sales for this project. Several studies incorporate measurements for similar concepts in the context of NPD budgeting. These studies see the return or the expected return of a product in development as a key driver for managerial decision-making prior to market commercialization. Deshmukh and Chikte (1977) optimize the stochastically changing return of a project as a key driver for the decision if and when to terminate a project. They measure the return of a development project as the product's terminal reward, defined as the expected discounted value of the resulting profit stream. That stream is modelled as a function of the product's quality in comparison to available products on the market. Prastacos (1983) develops a path of optimal sequential investment decisions under the consideration of convex or concave return functions. They define the concept as the expected return of the corresponding investment, without providing more details about the exact measurement. However, they define the measurement as a convex or concave increasing function of the investment size and the investment opportunity's quality. Loch and Kavadias (2002) allocate budgets to projects by taking into account multiple factors, such as uncertain market payoffs, or increasing or decreasing returns from the investment. They model the return of a project as its expected return on investment and include the possibility of changing return functions through different periods. Kavadias and Chao (2008) present a framework regarding resource allocation in new product development, in which they include a development project's return as a relevant influence factor on portfolio decision-making. They measure this return as the product's expected revenue after bringing it to the market.

Resources available is measured through the deviation between annual budgets and their forecasts during the year. The company had annual R&D spending budgets. Every three or four months, it published an internal report to estimate the expected resources that would be spent at the end of the year compared to the annual budget. We build our measurement on these reports: The more the forecast exceeds the budget, the more is spent on R&D in total. However, at the level of NPD projects, the implication is reverse. The more the forecast already exceeds the budget, the more difficult it will be to obtain additional resources for a specific project. So, the more the total forecast exceeds the total annual R&D budget, the lower the level of additional resource availability for individual NPD projects. We include data on the overall budget deviation from the most recent report to each day within our observation period. We also include a time lag, because decisions made on a specific day were often in preparation for several weeks or even months before they were actually made. We include data about resources availability for a longer period before the actual decision. Specifically, the final measurement for a specific decision is calculated as the average budget deviation for the last 90 days prior to a decision.

Several studies incorporate measurements for similar concepts regarding resource availability in the context of NPD budgeting. Adler et al. (1995) present a framework for analyzing development times in the context of multi-project development environments. In their stochastic processing network, they model human and technical resources as workstations that handle diverse development activities across different projects. They measure the available resources of these workstations with their respective hourly availability, which is incorporated as a limiting factor. Andries and Hünermund (2020) investigate how resource-abundant and resource-constrained firms are confronted with different consequences from a staged investment approach in innovation projects. In their empirical study based on data from 2,790 German firms, they measure the resource availability based on the company's credit rating according to a large German credit rating agency (Creditreform). Taggart (1987) proposes that limiting divisional budgets can be an economically reasonable approach, even if the top managers doing this, do not fully know the divisions' investment opportunities. The resources available per division are measured by the corresponding investment level in monetary equivalents.

Sunk cost is measured by dividing the resources already allocated to a project at t by the current NPD cost target of the project at the same time. The project's NPD cost target was also updated every three or four months. Several studies incorporate measurements for similar concepts, investigating the factor of sunk costs in the context of NPD budgeting. Schmidt and Calantone (1998) show that the sunk cost fallacy plays an important role in organizational NPD decision-making, especially when referring to projects with differing innovation levels. In their experiment, hypothetical development projects were considered at different stage gates that differed in their level of sunk costs. The level of sunk cost was measured as total money spent on the project until this point. Manez et al. (2009) empirically show that previous decisions that result in sunk costs matter for the way companies invest in R&D activities. They measure sunk cost as the overall amount of resources spent for R&D activities in the previous periods. Manez and Love (2020) give evidence that sunk costs for R&D activities are a key factor that leads to persistence in such activities. They measure sunk cost as the number of consecutive years a company invested in in-house R&D and also include information regarding the corresponding monetary amount.

Level of innovation is measured by dividing the number of newly developed parts in a project by the number of total parts. Thus, this variable applies to the project-level and does not vary across the separate decisions for the same project. Several studies incorporate measurements for the effect of a lower or higher level of innovation in the context of NPD budgeting. Chao and Kavadias (2008) investigate NPD portfolio management with strategic buckets by differentiating between radical and incremental innovation. They measure the level of innovation of a newly developed product as the number of new attributes that are included in a product, compared to the previously developed product. Huchzermeier and Loch (2001) incorporate performance variability in their study to investigate the value of managerial flexibility in NPD project management. This performance variability is closely connected to the technical novelty of a product and measured as the performance level of a new product. Schmidt and Calantone (1998; 2002) find that managers have a higher commitment to fund NPD projects that are more innovative in comparison to less innovative ones. In their experimental study (1998), they compare escalating commitment behavior for a hypothetical innovative new product and an incremental one. The products differed in their functionalities, as the innovative one offered substantial technological performance and safety advantages over the incremental one. In a subsequent study (2002), the same authors investigate differences in escalation behavior between radical and incremental innovation. In that study, they measure a product's level of innovation in dependence of its novelty to the market (i.e., radical innovation) or the company (i.e., incremental innovation).

5.4 Results

Results for the multiple linear regression are shown in Table 28. The regression model, as well as all independent variables, are significant to the level of .05. The adjusted R square of .153 shows that the selected variables explain a large share of the variance within compensation behavior.

Table 28: Result of the linear regression analysis of within-project NPD cost compensation

		Within-project NPD cost compensation			
		Unstandardized coefficients		Standardized coefficients	
	Expected sign	B	St. error	Beta	t
(Constant)		3.930	.914		4.301
Level of frontloading	+	.041	.005	$.334^{***}$	7.545
Financial project performance	−	-.111	.051	$-.091^{**}$	-2.173
Resources available	−	-.045	.016	$-.124^{***}$	-2.788
Sunk cost	−	-.032	.007	$-.201^{***}$	-4.288
Level of innovation	−	-.037	.008	$-.180^{***}$	-4.343
R^2			.161		
R^2 adjusted			.153		
F			19.922***		
n			526		

*p < 0.10; ** p < 0.05; *** p < 0.01

The results offer empirical support for factors that are associated with the use of the *compensation heuristic*. As expected, the *level of frontloading* is positively correlated with the NPD project cost compensation. This is consistent with the idea that the more a project is above the budget-allocation timeline, the more teams are motivated to look for possibilities to compensate resources within the project, aiming to reduce the gap towards the project's cost target. As expected, *financial project performance* is negatively correlated with the NPD project cost compensation. This is consistent with the idea that the better the overall expected financial soundness of a product is, the more easily it can afford additional costs and the less it is needed to find NPD cost compensation. Additional development activities can be included with additional resources. Also as expected, the *availability of resources* is negatively correlated with the NPD project cost compensation. This is consistent with the idea that the more financial means are at the disposal of the organization conducting the NPD project, the less compensation is done. Teams are less motivated to look for compensation and more likely to obtain additional resources. Thus, a greater need to compensate because of more frontloading, worse financial project performance, or fewer resources available is associated with more within-project NPD cost compensation.

Furthermore, *sunk costs* are negatively correlated with the NPD project cost compensation, as expected. This is consistent with the idea that the further the project progresses, and more resources have been allocated, fewer activities remain that could be altered and fewer degrees of freedom for altering these remain. Therefore, fewer options for compensation can be found. Also as expected, the *level of innovation* is negatively correlated with the NPD project cost compensation. This is consistent with the idea that it is more difficult for teams to find possibilities for cost compensation when they are working on more novel and difficult NPD projects. Thus, having fewer possibilities to compensate is associated with less within-project NPD cost compensation.

5.5 Discussion and conclusion

5.5.1 Theoretical implications

The results of this study show how the *within-project NPD cost compensation heuristic* can explain some of the organizational decision-making around budget allocation in NPD projects. The results support our hypotheses, which are based on the overall idea that more NPD project cost compensation is done as there is a greater need to compensate NPD costs and more possibilities exist for finding compensation. These results lead to three distinct contributions: first, we conceptualize the *compensation heuristic* in NPD project management; second, we provide evidence for factors that influence the use of this heuristic; third, we increase the understanding of ongoing budget allocation decision-making in NPD project management.

The first contribution of this study lies in the conceptualization of the *within-project NPD cost compensation heuristic*. Unexpected events are common in NPD and require managerial decision-making (Davila 2000; Santiago and Bifano 2005; Song and Montoya-Weiss 2001; Tatikonda and Rosenthal 2000; Um and Kim 2018). Heuristics are a way to make decisions in uncertain and complex business environments, such as NPD projects (Langerak et al. 2010; Sarangee et al. 2014; Stingl and Geraldi 2021; Sukhov et al. 2021; Tavares et al.; van Oorschot et al. 2011). Heuristics prioritize one dominant objective of an NPD project, such as NPD costs, NPD lead time, or product performance. Heuristics in this context do not aim for an optimal decision, but rather provide an efficient decision rule for teams in complex situations (Åstebro and Elhedhli 2006). This study contributes to the literature on managing uncertainty in NPD projects and on heuristics by introducing an additional heuristic, which focusses on within-project NPD cost compensation. Additional resources for development activities are required to react to events such as changes in market demands, technical challenges, or new information about competitors. How to finance these requirements during development, is a crucial question for decision-makers. We introduce the objective of compensating NPD project cost within the same project as a relevant and guiding motive in ongoing budget decision-making. The *compensation heuristic* improves our understanding about why and how decision-makers risk exceeding an NPD project's overall budget through the allocation of additional resources when confronted with unexpected events.

Our second contribution is the empirical investigation of factors associated with the *compensation heuristic*. We find that managers are more likely to compensate additional resources from within an NPD project if there is a greater need to compensate and more possibilities for finding compensation are available. Specifically, we find support for the hypotheses that within-project NPD cost compensation is positively related to the *level of frontloading* and negatively related to *financial project performance*, *resource availability, sunk costs*, and *level of innovation*. These factors have been shown to play a role for managing uncertain NPD projects, in particular as factors that may influence their resource allocation or the actual abandonment of projects on the basis of new, negative information. The level of frontloading is important in the context of NPD project management. It influences a project's option value and therefore has an impact on how decisions about further funding or abandonment are made during the project (Huchzermeier and Loch 2001; van Oorschot et al. 2010). Similar, an outlook on a product's financial performance is a main factor for decision-makers to select projects for a development portfolio (Loch and Kavadias 2002; Prastacos 1983) or to evaluate additional fundings for ongoing projects (Deshmukh and Chikte 1977). Availability of resources is another factor of relevance for the management of NPD projects. Most companies develop several products in parallel, which compete for scarce resources. The scarcity of these resources has an impact on the way projects are funded in general (Adler et al. 1995; Taggart 1987), and on ongoing budgeting decisions such as project abandonment in particular (Andries and Hünermund 2020). The sunk cost already invested in a development project is another factor relevant for ongoing budgeting decisions in NPD, since the decision of whether and how to invest additional resources to projects depends on the previous spending behavior (Manez et al. 2009; Manez and Love 2020; Schmidt and Calantone 1998). A product's level of innovation has an impact on managerial decision-making in terms of a higher commitment to more innovative products (Schmidt and Calantone 1998; Schmidt and Calantone 2002) as well as different funding strategies in general between products of different novelty degrees (Chao and Kavadias 2008; Huchzermeier and Loch 2001). We add to this literature by showing that these factors are conducive to the application of the *compensation heuristic,* as another approach for responding to unfavorable news about ongoing NPD projects.

Furthermore, we add to the literature on factors influencing the use of particular heuristics for decision-making in NPD projects. In particular, this applies to our variables financial project performance (Calantone et al. 1999; Venkatraman and Venkatraman 1995) as well as resource availability (van Roy and Gelders 1978). Beyond those, other variables are of interest in this context. A company's marketing abilities and the corresponding demand structures are relevant for heuristics in NPD decision-making (Calantone et al. 1999; Venkatraman and Venkatraman 1995; Vepsalainen and Lauro 1988). Similar, the development process itself and specifically the technical challenges and uncertainties during a project were brought forward as relevant influences in heuristic decision-making (Calantone et al. 1999; van Roy and Gelders 1978; Vepsalainen and Lauro 1988). The organizational context also plays a role in heuristic decision-making, especially regarding geographical differences of managers making relevant decisions (Gupta et al. 1992). Our study expands the understanding of factors that are relevant for the use of heuristics in NPD project management.

As the third contribution of this study, we improve the understanding of ongoing budget allocation decision-making in NPD projects. Allocating resources to NPD projects is a major success factor for those projects (Cooper and Kleinschmidt 1996). Research has considered decisions on allocating resources to an NPD project as an ongoing process, reacting to unexpected project-level events. Some studies propose models for the optimal dynamic funding path of an NPD project (Kester et al. 2011; Lint and Pennings 2001; Loch and Kavadias 2002; Messica and David 2000; Repenning 2001) but largely neglect to contribute empirical insights about how such decisions are made. Our study contributes uniquely to this understanding. Unexpected, unfavorable events happening during an NPD project may require new decisions about additional budget allocation. The *within-project cost compensation heuristic* highlights, that decision-makers must decide whether to allocate additional resources to a project, or have project teams find ways to compensate, so to use available resources from elsewhere within the project. Such resources could be available when favorable unexpected events make NPD activities easier in the sense of requiring fewer resources. New budget allocation decisions are made repeatedly during NPD projects as unexpected events occur. The heuristic helps to understand how decision-makers under cost pressure can respond to uncertainty, depending on the need and possibilities to find within project cost compensation.

5.5.2 Managerial implications

The first managerial implication of this study is the creation of awareness for the tension between adding additional budget for NPD costs versus requiring teams to compensate NPD costs within the same project. The *within-project NPD cost compensation heuristic* provides managers with an additional heuristic for reacting to unpredictable events during NPD projects. This is of special relevance in the context of ongoing resource allocation decisions: The single decisions within that context need to be managed individually for the avoidance of overspending in the corresponding NPD project. Since the overall resources spent at the end of a project is the sum of all budget allocation decisions made, managers could prioritize to avoid overspending based on a heuristic for managing NPD projects.

As second managerial implication, our study suggests how NPD cost compensation might be stimulated. We show that managers are more likely to compensate additional resources from within an NPD project if there is a greater need to compensate and more possibilities for finding compensation are available. Managers can take a more active role in the use of these factors, to influence their effect on single decisions. As an example, we could imagine a situation in which a company is in bad shape regarding available resources. More compensation within projects would be a desirable strategy to take some pressure out of the system. Our study showed us, that the availability of resources influences decision-makers' compensation behavior. In such a situation it might be beneficial to communicate the budgetary situation more actively throughout the company, so the information spreads to all stakeholders involved in resource decision-making. Also, it might be important to communicate the financial project performance, in particular when this is not so favorable, to stimulate teams to more actively try to compensate NPD cost overruns within their project.

5.5.3 Limitations and future research

This original piece of research is subject to limitations. First, the empirical study to test our conceptualization of the *within-project NPD cost compensation heuristic* and the corresponding hypothesis is based on a limited database. We had the opportunity to get access to rich and diverse data from the case company. However, this data was limited to nine development projects and the budget allocation decisions within them. A broader set of decisions to analyze from diverse organizational environments could help gain further evidence for our concept. The second limitation we want to point out are potential inaccuracies in the measurements of the variables. We made a series of assumptions to measure our constructs. Examples are the budget authorization timeline or the selection criteria of five percent to distinguish between planned and unplanned budget allocation decisions. Although we made these assumptions to the best of our knowledge, we had to accept a certain degree of simplification.

The introduction of the *compensation heuristic* opens a wide range of future research possibilities. The first research direction we propose is the investigation of further influence factors that are relevant for the *compensation heuristic*. The independent variables in our empirical study explain a share of the compensation's variance but leave room for additional factors of relevance. Factors such as market demand structures or the geographic decision-making context have been subject to previous studies on heuristics in NPD (Gupta et al. 1992; Venkatraman and Venkatraman 1995). Exploring the influence of such additional factors on the *within-project NPD cost compensation heuristic* would increase our understanding of heuristic organizational decision-making.

Second, we suggest an expansion of the *compensation heuristic* to other financial elements of a product's business case, revenues in particular. In NPD, decisions must be made under consideration of various restrictions across different cost- and revenue types. Aspects such as a product's sales potential or its price position have shown to be relevant in the context of heuristics in venture capital investments (Åstebro and Elhedhli 2006) but are so far largely neglected in our concept. Expanding the cost compensation problem to a more holistic trade-off between cost and revenue consequences seems worthwhile exploring, as this would increase our understanding about ongoing decision-making in NDP projects.

As third promising research possibility, we suggest thinking about other investment scenarios outside of NPD in which compensation plays a role. Such scenarios might be venture capital investments or construction projects, where the application of heuristics was shown to be a relevant approach (Åstebro and Elhedhli 2006; Bingham and Eisenhardt 2011; Eriksson and Kadefors 2017). Compensation in such situations would relate to the shifting of existing funds within a venture or a construction project, instead of approving additional resources when faced with specific challenges. Imagine a scenario in which a venture's expansion to a new sales region suddenly is necessary since a competitor recently started business there. The venture capital investor could allocate additional resources for that purpose or could ask the venture to compensate by using available funds, even if those were originally assigned for another purpose. In construction projects, similar scenarios are thinkable, for example, if the construction team discovers that the underground for a bridge's foundation is not as solid as expected, making the use of specialized equipment necessary. The management would have to decide whether they want to allocate additional resources to cover for that equipment or shift funds predetermined for other parts of the construction project, to avoid additional spending. It would be enlightening to see whether the concept can be generalized beyond NPD projects.

6 Conclusion

The purpose of this dissertation was to improve our understanding of the management of costs of new product development projects. To shed light on this topic, we were able to conduct four studies. The first three studies – a literature review, a method-oriented study, and a qualitative case study – contribute to the research topic of NPD cost estimation. The last study – an empirical study based on proprietary archival data – concerns the ongoing decision-making process during NPD projects. In this concluding chapter, we summarize this thesis' studies, emphasize their contributions, and point our limitations as well as promising areas for future research.

Our literature review on NPD cost estimation methods summarizes the scientific status quo regarding this topic. The systematic review approach allowed us to find 39 publications, that deal with methodological NPD cost estimation. We showed that these studies present a large variety of different cost estimation techniques for this purpose. Following the cost estimation method classification scheme of Niazi et al. (2006), we identified the following techniques as most common for NPD cost estimation: *parametric methods, regression analysis models, activity-based costing,* and *back-propagation neural networks*. We pointed out that the combination of multiple techniques is a regular motive to achieve better results. We also shed light on several practical aspects relevant to NPD cost estimation. First, we give guidelines for the successful setup, the application, and the maintenance of an NPD cost estimation method. Second, we conclude that despite the high level of uncertainty being repeatedly named a threat to NPD cost estimation, few scholars actively include solutions in their approaches. Third, we summarize challenges in the context of data availability: we conclude that the usually small amount of comparable data is one of the biggest, if not the biggest, challenge in NPD cost estimation.

In our second study, we add the *NPD cost benchmarking method* to the body of literature on NPD cost estimation methods. So far, external cost data had scarcely been used for the estimation of NPD costs (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). The novel approach builds on publicly available data to estimate NPD costs on product level based on competitors' cost data. After extracting and adjusting NPD cost information from competitors' annual reports, it is combined with the number of products developed per year of the observation period. With this information a regression model is set up, that delivers the average NPD costs estimated for defined project types. The method seamlessly fits into the existing approaches for NPD cost estimation by combining regression analysis with a parametric component (e.g. Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009). Like this, we contribute a novel take on the data availability problem in NPD cost estimation.

In the third study of this dissertation, we shed light on practical challenges that arise in organizational NPD cost estimation, and especially with the application of the *NPD cost benchmarking method*. For this purpose, we conducted a qualitative case study at an automotive company. The author of this thesis was involved in the implementation, application, and maintenance of the *NPD cost benchmarking method* in the said firm. Building on observations, documents, communications, and discussion-style interviews, the study delivers a comprehensive picture of the challenges of NPD cost estimation. We show that active change management, which was shown to be beneficial in general change processes (Burnes and Jackson 2011; By 2005; Gill 2002), can improve the credibility of a newly introduced NPD cost estimation method. We also show that the combination of regression models and parametric approaches, which is common in the NPD cost estimation literature (Bashir and Thomson 2001; Bashir and Thomson 2004; Chen et al. 2019; Li et al. 2009; Salam et al. 2009), is particularly credible for NPD cost estimation due to its well-suited level of explainability. Regarding the credibility of the *NPD cost benchmarking method* in particular, we find that it is best used as a tool for the strategic planning of a development portfolio, while it lacks credibility for short-term estimations, as well as for estimations of modular structures. We unveil the comparability problem as the main challenge when building on external data for NPD cost estimation purposes. Such approaches that build on external data, as an alternative to the dominant focus on internal data, were proposed by few authors (Carreyette 1977; Chen et al. 2010; Chen et al. 2020b). Regarding the generally poor quality of data available for NPD cost estimation, we find that this challenge is not as critical as often assumed (Carreyette 1977; Chen et al. 2020b; Harrold and Nicol 1977; Mousavi et al. 2015), also because we see that expert knowledge can often sufficiently replace data of poor-quality. This emphasizes the importance of such expert knowledge in the context of NPD cost estimation (Adelberger and Haft-Zboril 2015; Holtta-Otto and Magee 2006; Riedrich and Sasse 2005; Roy et al. 2001; Scanlan et al. 2006).

Our fourth study shows how the conceptualized *within-project NPD cost compensation heuristic* (hereinafter also *compensation heuristic*) explains some of the organizational decision-making around budget allocation in NPD projects. The first contribution of this study lies in the conceptualization of the *compensation heuristic*. Unexpected events are common in NPD and require managerial decision-making (Davila 2000; Santiago and Bifano 2005; Song and Montoya-Weiss 2001; Tatikonda and Rosenthal 2000; Um and Kim 2018). Heuristics are a way to make decisions in uncertain and complex business environments, such as NPD projects (Langerak et al. 2010; Sarangee et al. 2014; Stingl and Geraldi 2021; Sukhov et al. 2021; Tavares et al.; van Oorschot et al. 2011). The *compensation heuristic* improves our understanding of why and how decision-makers risk exceeding an NPD project's overall budget through the allocation of additional resources when confronted with unexpected events. The second contribution of our fourth study is the empirical investigation of factors associated with the *compensation heuristic*. We find that managers are more likely to compensate additional resources from within an NPD project if there is a greater need to compensate and more possibilities for finding compensation are available. As the third contribution of our fourth study, we improve our understanding of ongoing budget allocation decision-making in NPD projects. Some studies propose models for the optimal dynamic funding path of an NPD project (Kester et al. 2011; Lint and Pennings 2001; Loch and Kavadias 2002; Messica and David 2000; Repenning 2001) but largely neglect to contribute empirical insights about how such decisions are made. The *compensation heuristic* highlights, that decision-makers must decide whether to allocate additional resources to a project, or have project teams find ways to compensate (i.e., to use available resources from elsewhere within the project). The *compensation heuristic* helps to understand how decision-makers under cost pressure can respond to uncertainty, depending on the need and possibilities to find within project cost compensation.

As each study is subject to limitations, this dissertation also has certain boundaries. In the literature review study, we cannot guarantee that we included all relevant and only high-quality literature due to the research design. An overarching limitation for the remaining three studies is a potential bias, due to the researcher's active part in the case company. The qualitative case study bears limitations that come with the research design: As only a single case during a certain period is observed, generalization might be challenging. The empirical part of the fourth study is subject to limitations concerning the amount of data from the underlying database as well as possible inaccuracies due to the measurements of variables.

Our dissertation sheds light on the complex and uncertain world of NPD cost management. It unveils several streams for promising research. First, we concluded that the number of available methods for NPD cost estimation is still scarce compared to the importance of the topic. This calls for new and innovative approaches. How to deal with the challenges of uncertainty and data availability should be of high focus for future scholars. Second, our understanding of the *NPD cost benchmarking method* could be improved by implementing and investigating the concept in other organizational environments. The third major stream we hope future scholars will work on is the ongoing budgeting decision-making in NPD. Here, we propose to expand the concept of the *compensation heuristic* by investigating further influence factors and other organizational environments.

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Appendix

Appendix A: Publications in final set summarized by literature stream, publication type, and rating (detailed)

Table 29: The final set of our literature review summarized by literature stream, publication type, and rating (detailed)

Publications per literature stream and publication type	Number of publications	Publication rating[a]
Engineering	**28**	**0.47**
Book series	1	0.11
Applied Mechanics and Materials	*1*	*0.11*
Conferences and proceedings	9	0.19
19th International Conference on Industrial Engineering and Engineering Management	*1*	*0.18*
2012 International Conference on Intelligent Systems Design and Engineering Application	*1*	*not listed*
Procedia Engineering	*2*	*0.28*
Proceedings of ICED 2007, the 16th International Conference on Engineering Design	*1*	*0.16*
Proceedings of IEEE International Conference on Grey Systems and Intelligent Services, GSIS	*2*	*0.12*
Proceedings of the 2013 Joint International Conference on Rural Information and Communication Technology and Electric-Vehicle Technology, rICT and ICEV-T 2013	*1*	*not listed*
Proceedings of the International Conference on Engineering Design, ICED	*1*	*0.16*
Contract research reports	1	not listed
Rand Corp Rep R-1693-1-PA&E	*1*	*not listed*
Journals	17	0.61
Aeronautical Journal	*1*	*0.29*
Chinese Journal of Aeronautics	*1*	*0.75*
Computers and Industrial Engineering	*1*	*1.33*
Concurrent Engineering: Research and Applications	*1*	*0.55*
Design Studies	*2*	*0.96*
Entwerfen Entwickeln Erleben	*1*	*not listed*
Expert Systems with Applications	*1*	*1.19*
IEEE Access	*1*	*0.61*
International Journal of Industrial Engineering: Theory Applications and Practice	*1*	*0.35*

Table 29: The final set of our literature review summarized by literature stream, publication type, and rating (detailed) (continued)

Publications per literature stream and publication type	**Number of publications**	**Publication rating[a]**
Journal of Aircraft	*1*	*0.41*
Journal of Engineering Design	*2*	*0.65*
Journal of Intelligent & Fuzzy Systems	*1*	*0.41*
Konstruktion	*1*	*0.10*
Research in Engineering Design - Theory. Applications. and Concurrent Engineering	*1*	*0.44*
The Naval Architect	*1*	*0.10*
Engineering & management	**3**	**0.83**
Journals	3	0.83
IEEE Transactions on Engineering Management	*2*	*0.83*
IRE (now IEEE) Transactions on Engineering Management	*1*	*not listed*
Management	**6**	**0.29**
Conferences and proceedings	1	not listed
2009 8th International Conference on Reliability, Maintainability and Safety (ICRMS 2009)	*1*	*not listed*
Journals	5	0.29
American Society of Mechanical Engineers Paper	*1*	*not listed*
CON (Controlling)	*2*	*not listed*
Foundations of Management	*1*	*0.20*
International Journal of the Economics of Business	*1*	*0.39*
Production	**2**	**2.05**
Journals	2	2.05
International Journal of Production Economics	*1*	*2.48*
Journal of Cleaner Production	*1*	*1.62*
Overall	**39**	**0.58**

[a] Average publication rating according to SCImago Journal Rank 2018

Appendix B: Regression model for *Mobility SE*

Table 30: Input data for the regression analysis model for the baseline estimation of our numerical example (*Mobility SE*)

	List of Projects developed			
Year *t*	$\#DPT_{At}^{Mobility\ SE}$	$\#DPT_{Bt}^{Mobility\ SE}$	$\#DPT_{Ct}^{Mobility\ SE}$	$SPENDING_{t}^{Mobility\ SE}$
2001	1.8	3.2	13.9	1.875 mEUR
2002	1.6	3.45	12.25	1.783 mEUR
2003	1.8	3.25	11.8	1.780 mEUR
2004	1.9	3.1	11.95	1.780 mEUR
2005	2	3	12	1.780 mEUR
2006	2	3	12	1.780 mEUR
2007	2	3	12	1.780 mEUR
2008	2	3	12	1.780 mEUR
2009	2	3	12	1.780 mEUR
2010	2	3	12	1.780 mEUR
2011	2	3	12	1.780 mEUR
2012	2	3	12	1.780 mEUR
2013	2	3	12	1.780 mEUR
2014	2	3	12	1.780 mEUR
2015	2	3	12	1.780 mEUR
2016	2	3	12	1.780 mEUR
2017	2.00	3.20	11.70	1.780 mEUR
2018	2.00	3.65	10.70	1.780 mEUR
2019	2.00	3.90	10.10	1.885 mEUR

$$\begin{pmatrix} 1.875 \\ 1.783 \\ 1.780 \\ \vdots \\ 1.885 \end{pmatrix} = \begin{pmatrix} 1.80 & 3.20 & 13.9 \\ 1.60 & 3.45 & 12.25 \\ 1.80 & 3.25 & 11.80 \\ & \vdots & \\ 2.00 & 3.90 & 10.10 \end{pmatrix} * \begin{pmatrix} COST\ DPT_{DPT\ A}^{MOBILITY\ SE} \\ COST\ DPT_{DPT\ B}^{MOBILITY\ SE} \\ COST\ DPT_{DPT\ C}^{MOBILITY\ SE} \end{pmatrix} \tag{4}$$

Formula 4: Regression model for baseline estimation in numerical example (*Mobility SE*)

Table 31: Result of the linear regression analysis of our numerical example (*Mobility SE*)

	Linear regression model for baseline (*Mobility SE*)		
	Unstandardized coefficients		
	B	St. error	t
$COST\ DPT_{DPT\ A}^{Mobility\ SE}$	243.233***	26.121	9.312
$COST\ DPT_{DPT\ B}^{Mobility\ SE}$	199.04***	12.160	16.370
$COST\ DPT_{DPT\ C}^{Mobility\ SE}$	57.885***	3.776	15.331
R^2	1.00		
R^2 adjusted	1.00		
F	6.6617.920***		
n	19		

*p < 0.10; ** p < 0.05; *** p < 0.01