Management Accounting during New Product Development:
A Case Study Mitigating Financial Tradeoffs for Modular Products

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften

Dr. rer. pol.

von der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

Dissertation

von

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Tag der mündlichen Prüfung:	28.07.2026
Erster Gutachter:	Prof. Dr. Marc Wouters
Zweiter Gutachter:	Prof. Dr. Albert Albers
Karlsruhe	15.06.2026

“Theory without practice is empty; practice without theory is blind.”
– Adapted from Immanuel Kant (Critique of Pure Reason, A 51 / B 75)

To my beloved mother, father, and grandparents!

Summary

This dissertation addresses the topic of financial tradeoffs during new product development (NPD). To address this challenge, the present work provides actionable insights into managing these tradeoffs. We[1] divide this doctoral thesis into three main chapters that address the research topic from two perspectives. The first perspective focuses on mitigating financial tradeoffs through product architecture decisions (Chapter 2) and maximizing benefits through target costing and cost-effectiveness analyzes (Chapter 3). The second perspective examines the reliability of contribution margin forecasts (Chapter 4) and thus investigates the pressure to mitigate financial tradeoffs.

The first main chapter provides a broad overview of financial tradeoffs during NPD and the role of product architecture decisions therein. We conduct an integrative literature review and contribute to the current state of research in two ways. First, we identify financial tradeoffs that arise from the conflicting objectives of optimizing a product's revenue, functionality and performance, direct costs, development overhead costs, and lead time – both at the individual product level and at the intersection with the overarching project level. By placing these tradeoffs at the center of the review, we provide a new perspective and develop a conceptual framework that maps these tradeoffs. Thereby, we highlight the mechanisms through which product architecture decisions in the form of modular product design influence the identified financial tradeoffs.

The second main chapter focuses on the scenario in which, contrary to scientific assumptions, the gap between allowable and realizable costs cannot be closed by cost management activities. As a result, financial tradeoffs become inevitable – an issue for which prior research provides only limited guidance. Considering target costing and cost-effectiveness – the additional property points per additional direct cost – we present a practical approach to maximize product properties while adhering to target costs. The approach configures the product in three successive steps. First, it establishes a segment-specific minimum product based on a predecessor product accounting for learning effects and cost benchmarks. Second, it incorporates mandatory components from commonality strategies. Third, it exploits further configurational options based on their cost-effectiveness using one out of three presented prioritization logics.

The third main chapter uses a proprietary archival dataset to analyze the influence of individual determinants – *Time Effects*, *Production Effects*, and *Segment Importance* – on the accuracy of forecasts related to the contribution margin of development projects. Both the approach and the findings from the correlated random effects regression analysis provide added value to the academic discussion. We identify significant predictors related to the contribution margin accuracy. Our study thereby complements results from earlier research, which is predominantly based on experimental or survey-based approaches, by providing empirical evidence from archival company data.

[1] For stylistic consistency, the first person plural perspective is employed throughout the thesis. Notwithstanding this editorial convention, the thesis reflects the independent work of Eduard Sebastian Kepl, conducted without any impermissible third party assistance.

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Abbreviations

A

AC · *Allowable Cost*
ACEA · *European Automobile Manufacturers' Association*
ARP · *Attainable Retail Price*

B

BIC · *Best In Class*
BMW · *Bayerischen Motoren Werke*
BoBP · *Best of Budget Product*
BPLM · *Breusch-Pagan-Lagrange-Multiplier*

C

C · *Property Comfort*
CG · *Cost Gap*
CM · *Contribution Margin*
CRE · *Correlated Random Effects*

D

D · *Property Driving Dynamics*
DC · *Direct Cost*
DR · *Drifting Cost*

E

E · *Property Environmental Compatibility & Sustainability (E)*
EC · *European Commission*
ECC · *European Car Corporation*
EoE · *Economies of Efficiency*
EoL · *Economies of Learning*
EUR · *Euro*

F

FE · *Fixed Effects*
FEr · *Forecast Error at time t*

G

GLS · *Generalized Least Squares*

I

IBC · *In Best Class*
IOM · *Innovation and Operations Management*
I_{Pr} · *Property Importance*

L

LIC · *Last In Class*

M

MA · *Management Accounting*

N

NPD · *New Product Development*
NR · *Net Revenue*

O

OEM · *Original Equipment Manufacturer*
OLS · *Ordinary Least Squares*

P

PDP · *Product Development Process*
PP · *Property Points*
PPDP · *Product Platform Development Project*
PPG · *Property Points Gap*
PPI · *Property Point Increment*
PPP · *Product Property Profile*
PTC · *Product Target Cost*

Q

Q · *Property Quality*
QFD · *Quality Function Deployment*

R

R · *Financial Return*

R&D · *Research and Development*
RE · *Random Effects*
RPP · *Reached Property Points*

S

S · *Property Suitability for Everyday Use*
SSEP · *Segment-Specific Enrichment Product*
SSMP · *Segment-Specific Minimum Product*
SV · *Sales Volume*

T

TCM · *Target Contribution Margin*
TR · *Target Return*

U

ULIC · *Under Last In Class*
USA · *United States of America*

V

VIF · *Variance Inflation Factor*

W

WTP · *Willingness to Pay*

Preface and Acknowledgment

The following dissertation is the result of a collaboration between the Chair of Management Accounting at the Karlsruhe Institute of Technology and a leading automotive company. The thesis is of interest to academics and practitioners interested in the fields of cost management, product development, modular products, and contribution margin forecasting.

At the end of 2021, I was in the final stage of my Master's thesis and was faced with the question: What happens next? Fortunately, I came across the job advertisement for a research associate at Karlsruhe Institute of Technology in collaboration with the automotive industry with the aim of writing a Doctoral’s thesis. The job description seemed to me like a unique opportunity to gain industrial experience as well as to advance my education. In short, I decided to apply for the three-year program and was delighted to be given the extraordinary opportunity to prove myself in this setting between industry and science. In retrospect, I can now conclude that this was also the best possible decision I could have made.

First and foremost, I would like to thank Professor Dr. Marc Wouters for giving me this opportunity and for the constructive as well as instructive collaboration. Dear Marc, without your valuable support and your detailed feedback, this thesis would not have been possible. Since my employment at your chair, I have been able to learn a lot about scientific work and the continuous improvement of my work. Besides, I learned to ask the right questions, investigate deeply on a subject, challenge the status quo, and most importantly to always stay curious and never give up! Thank you very much for your support throughout the entire course of the thesis and the close, regular, and inspiring supervision. I cannot thank you enough for allowing me to write my dissertation under your supervision in this unique setup built on trust, respect, and encouragement. Your enthusiasm for research and attention to detail are unmatched and were an inspiring driving force for me throughout the entire journey!

I would also like to thank my colleagues at the Chair of Management Accounting, Ms. Nadine Fleischer, Mr. Philip Dickemann, Mr. Niklas Letmathe, Mr. Sören Jaedeke and from the Dean’s office, Ms. Eve Weiss. Dear Nadine, your caring nature made the organization of the thesis much easier for me and made every visit to Karlsruhe even more enjoyable. Dear Ms. Weiss, your availability and eagerness to help in the submission process deserves special recognition. Dear Philip, dear Niklas, I was always very happy about the regular exchange on site in Karlsruhe, and I wish you every success in the academic career you are pursuing. Besides, I would especially like to thank my fellow sufferer aka partner in crime. Dear Sören, I am incredibly grateful not to have gone down the path of an industrial doctorate alone, but with you at my side. The personal and frequent exchange was of immeasurable value to me. You were a real support throughout the past years and a personal benchmark I was always happy to consult. You always added joy to the joint journey we both chose after our Master’s degree, and I am delighted that I can call you not only a colleague but also a true friend!

Furthermore, I would also like to thank the project initiators at senior and top management level, Mr. Karsten Everding, Dr. Stefan Niemand, Mr. Jörg Felten, and Mr. Kai Siedlatzek. I remember very well my interview at the time and my joy when I received the news that I would be working

for your company as part of the industrial promotion program. Besides, I would also like to thank Mr. Axel Römer for taking over the program in its second half. The semi-annual status presentations at which I was able to present the status as well as progress of my doctoral thesis and the valuable feedback generated thereof were a particularly noteworthy addition to my doctoral program, for which I would like to thank you as a whole. Dear Karsten, I remember very well how you appreciated my engagement at the Quick Check in the first part of the projects and dedicated special sessions to precisely align the dissertation topic in the projects' second half. Therefore as well as for allowing me to find my home department on the awesome FE-G1 team, I would like to take this opportunity to thank you once again.

Talking about my FE-G1 team, I would like to take this opportunity to expressly thank them for the outstanding cooperation and the pleasant team atmosphere. Moreover, I would like to particularly thank my managers, Mr. Fabian Ohm, and Mr. Stefan Grunenberg as well as my colleague Mr. Sebastian Vahle. Dear Fabian, thank you very much for allowing me to prove myself during the Quick Check and learn basic information about direct material costs, modular toolkits, and modules. Dear Stefan, thank you very much for your support in concretizing my thesis, your ubiquitous availability, your regular feedback and your backing with the target vehicle. Your support and interest in my topics deserves special recognition and I am grateful to have profited from it. Dear Sebastian, you have an incredible wealth of knowledge and are always open to sharing and supporting your fellow workers. Thank you so much for your incredible support, for taking me by the hand from the very beginning and for the countless conversations I was able to have with you. Without your support and the exchange with you, my thesis would have been many times more difficult.

Furthermore, I would also like to thank my predecessors, Dr. Frank Stadtherr, Dr. Dominik Hammann, and Dr. Michael Disch. Dear Dominik and Michael, hereby I would like to express a special note of appreciation for your extraordinary support throughout the whole program. Even before my official start, I was able to get to know you and openly discuss information about the program. Over the past years, you have always offered yourselves as discussion partners and provided me with enormous support, both scientifically, professionally, and personally, which was of unmeasurable value to the success of this thesis.

Likewise, I would also like to express my gratitude for the chapter specific support in the form of expertise and data. For my third chapter, I want to thank Mr. Tobias Roß and Mr. Nils Sedlmaier for their openness, expertise and general support concerning product properties. For my fourth chapter, I would like to thank Mr. Julius Voigt and Dr. Marc Helmer for the pleasant and unbureaucratic way of data generation.

Last but not least, I would like to thank my mother, my father, my grandparents, and my close friends. Not only during my dissertation, but also in preparation for my studies, you always gave me your full support, cheered me up and enabled me to go my own way. I am incredibly grateful for this support and opportunity, because without you I would not be in the position in life that I am fortunate enough to be in now!

Karlsruhe, 2026
Eduard Sebastian Kepl

1 Introduction

The subsequent introductory chapter establishes the basis of this doctoral thesis by delineating its targeted research areas, structural outline, and principal contributions. It furthermore offers a brief, top-level overview of the main chapters, each representing a distinct contribution to the designated research areas. For stylistic consistency, the first-person plural perspective is employed throughout the thesis. Notwithstanding this editorial convention, the thesis reflects the independent work of Eduard Sebastian Kepl, conducted without any impermissible third-party assistance, for which the author bears full responsibility.

This dissertation explores the management of financial tradeoffs in new product development (NPD) as overarching research topic. Competitive markets require companies to offer a highly adaptable product while keeping their total costs low to secure profitability (Kampker et al., 2012). Decisions during the early phases of NPD are a crucial determinant of a company's future success, as between 70 and 80 percent of a product's costs are predetermined at that stage (Chase, 2001; Rush and Roy, 2000). Typically, resources in the product development process (PDP) are limited and not sufficient to realize all aspired development goals, which may be in tension with one another. These situations create tense tradeoff situations that require decision-makers to choose among either favoring or balancing product- and project-related success factors such as NPD lead time, revenue, quality, and costs (Thore Olsson et al., 2018). In this dissertation, we conceive financial tradeoffs during NPD as situations in which a minimum of two financially relevant project objectives cannot be optimized simultaneously. Given that financial tradeoffs are omnipresent during NPD, we place them at the center of this doctoral thesis and analyze them from two distinct research perspectives. The first perspective focuses on how financial tradeoffs during NPD can be actively managed – either by mitigating them through product architecture decisions (Chapter 2) or by maximizing the benefits achievable within given cost constraints (Chapter 3). The second perspective examines the reliability of the cost information on which cost management activities rely and thereby investigates the pressure to mitigate financial tradeoffs in the first place (Chapter 4).

In the first research perspective, the mitigation of financial tradeoffs plays a central role for our thesis. Chapter 2 investigates the mitigation of financial tradeoffs through product architecture decisions – particularly the choice of a modular product design. Modular product design is a strategy and cost management method to serve customers' desire for individualized and diversified products at costs similar to those of mass products (Wouters and Morales, 2014). Economies of scale and scope are realized by combining a limited number of modules to create a large number of similar, yet diversified and differentiated, products for the customer. Modularity has (re)gained importance as many industries have shifted towards buyers' markets with intense competition and small margins (Kampker et al., 2012). Understanding how product architecture decisions reposition the tradeoffs that decision-makers face is therefore of high practical and academic relevance addressed in our integrative literature review. Chapter 3 complements this architectural lens by investigating how the benefits within given financial boundaries can be maximized through an extension of target costing and cost-effectiveness analysis. Rather than assuming that the cost gap between allowable and realizable product costs is ultimately closable through conventional cost management activities (Ax et al., 2008; Ellram, 2002), we develop a pragmatic approach that identifies the best realizable product within the given financial boundaries. We base our method-oriented approach on a predecessor product as most new products are essentially not a completely new greenfield product but usually a new product generation (Albers et al., 2016).

The second perspective examines the reliability of financial information on which these tradeoff management activities rely and thereby investigates the pressure to mitigate financial tradeoffs in the first place. This perspective is addressed in Chapter 4, which investigates the determinants of forecast accuracy of the contribution margin from NPD projects. Accurate contribution margin forecasts are a critical success factor for companies to understand which projects to approve, where to invest corporate resources, and how severely financial tradeoffs bind. If these forecasts are unreliable, decision-makers cannot assess the actual magnitude of the cost gap, and the pressure to mitigate financial tradeoffs may be either over- or underestimated. Despite this importance, empirical knowledge on what drives forecast accuracy remains scarce, as companies are not required to disclose such sensitive information (Disch, 2024; Jordan and Messner, 2020). We address this research gap by capitalizing on a proprietary archival cost dataset obtained through our partner company, the automotive company European Car Corporation (ECC).

To investigate these research topics, we draw on a multi-method research design and divide this dissertation into five chapters. Besides this introductory chapter, the thesis comprises three main chapters that address the above outlined research areas as well as a concluding chapter. All three studies are grounded in a longitudinal engagement at ECC, where the author was an on-site full-time team member of the management accounting department for a period of three years. This privileged setup provided access to various information sources and forms ranging from sensitive financial data over personal discussions with cost experts and engineers in meetings, calls, mails or chats to day-to-day target costing work and informal exchanges at the coffee machine. The first study employs an integrative literature review that synthesizes diverse streams of research into a conceptual framework. While this review does not draw on ECC-specific data, the topics observed in the day-to-day work at ECC served as a central source of inspiration. The second and third studies are grounded more directly in the empirical reality of ECC. The second study follows an action research design in which the target costing extension was developed iteratively in conjunction with ECC practitioners, while the third study capitalizes on a unique proprietary archival dataset obtained through our engagement at ECC. The close collaboration with practitioners ensured that the developed methods are grounded in practical relevance while contributing to academic knowledge. Combined with our research-based analytical perspective on upcoming challenges, we are able to bridge the gap between an emic and etic research perspective (Jönsson and Lukka, 2006; Lukka and Wouters, 2022; Suomala et al., 2014).

In the following, we briefly summarize the three main chapters, i.e. the integrative literature review, the method-oriented study, and the proprietary archival data study. Figure 1 schematically presents the structure of this thesis.

Figure 1 – Structure of the Doctoral Thesis

The second chapter presents an integrative literature review on financial tradeoffs during NPD and the impact of product architecture decisions. We position our literature review at the intersection of product design, financial tradeoffs, cost management, and product development. Given that modular product design is a thoroughly researched topic (Frandsen, 2017), we choose to conduct an integrative literature review that creates a conceptual framework of financial tradeoffs during product development and product architecture impacts thereon (Snyder, 2019; Torraco, 2016, 2005). Whilst not claiming a full review of papers in our research field, we alone summarize 41 existing literature reviews and review numerous papers published in more than 57 distinct journals and book chapters. To synthesize our findings, we build on and extend the tradeoff framework of Wouters et al. (2016) by adding further tradeoffs and by systematically examining the role of product architecture. By placing these tradeoffs at the center of the review, we provide a new perspective with a deliberate section of the literature review per identified tradeoff and an analysis on the project as well as product level. This clearly sets our review apart from existing contributions that usually discuss tradeoffs as one out of many distinct aspects to be considered during the individual phases of a product's lifecycle (Labro, 2004; Wouters and Stadtherr, 2017). The chapter concludes with a critical assessment of the evidence base, revealing a severe imbalance between analytical modeling and empirical financial validation across all identified tradeoffs.

The third chapter is characterized as method-oriented study and contributes a practically applicable approach to steer product development from a management accounting perspective once the cost gap between allowable and realizable product costs cannot be closed. In an action research based setup at ECC (Checkland and Holwell, 1998; Formentini and Romano, 2011), we develop a practically applicable approach that uses a three-stage product configuration process. Starting from a predecessor product and its cost base, the first stage creates a segment-specific minimum product by incorporating economies of learning, economies of efficiency, cost benchmarks, and legal requirements. The second stage enriches this product with mandatory components arising from commonality strategies. In the third stage, further technical product enrichment activities are selected based on cost-effectiveness – i.e. the additional property points per additional direct cost – until the allowable cost budget is fully exploited. We present three optimization approaches and illustrate them with a fictional yet realistic numerical example. The chapter thereby provides a pragmatic method for decision-makers who need to identify the best realizable product within given financial boundaries and design restrictions.

The fourth chapter presents a proprietary archival study on the forecast accuracy of the contribution margin from real NPD projects. Drawing on a unique dataset of 43 completed development projects at ECC, we employ a correlated random effects regression approach to analyze the influence of the potential determinants labelled as *Time Effects*, *Production Effects*, and *Segment Importance* (Bell and Jones, 2015; Schunck, 2013; Schunck and Perales, 2017; Wooldridge, 2013). Our findings reveal that *Production Effects* significantly affect forecast accuracy, with inhouse-produced products being more accurately forecasted than externally sourced ones. The relationship between *Segment Importance* and forecast accuracy is partly significant, with the lowest-volume segment exhibiting significantly less accurate forecasts. *Time Effects*, contrary to theoretical expectations, show no significant influence in our dataset. The chapter contributes first-hand insights into real-world forecasting practices based on proprietary data that typically remains undisclosed.

2 Financial Tradeoffs during New Product Development: An Integrative Literature Review

Abstract

Competitive markets require companies to offer a highly adaptable product while keeping their total costs low to secure profitability. Decisions during the fuzzy front end of new product development (NPD) are a crucial determinant of the company's future success as a high share of the total costs is predetermined at that stage. These early decisions create tradeoff situations that require decision-makers to choose among either favoring or balancing product- and project-related success factors such as NPD lead time, revenue, quality, and costs. Product architecture decisions – particularly modular product design – significantly affect how companies handle these financial tradeoffs. Using an integrative literature review, we place financial tradeoffs at the center of our review activities and answer the following questions: "What financial tradeoffs arise around the development of new interdependent products?" and "What is the impact of product architecture decisions on these financial tradeoffs?". We answer these questions by developing a conceptual framework consisting of three models. A tradeoff model illustrating product and project level tradeoffs driven by an overall profit maximization target. An impact model illustrating the architecture impacts through modularization grouped by variety management, manufacturing flexibility, and design options. An impact strength model driven by volume considering distinct degrees of modularization.

Keywords: Modular Product Design; Product Architecture; Decision-Making; Financial Tradeoffs; New Product Development

2.1 Introduction

Modular product design is known as a strategy and cost management method to serve customers' desire for individualized and diversified products at costs similar to those of mass products (Wouters and Morales, 2014). Economies of scale and scope are realized by combining a limited number of modules to create a large number of similar – yet diversified and differentiated – products for the customer. Due to the increased market offerings available to potential customers and their easy access to information, many industries have shifted towards buyers' markets, where competition is intense and margins are small. Under these circumstances, it is essential for manufacturing companies pursuing a sustainable business strategy to develop a cost-effective product portfolio. Strategies like modular product design have consequently (re)gained importance (Kampker et al., 2012).

Modular product design is not a new topic (Fixson, 2007). Salvador's (2007) overview of different definitions concerning product modularity shows that modular design has been discussed in scientific research since the 1960s. The fact that modularity has been studied across diverse subject areas – “from mathematics to psychology” (Frandsen, 2017, p. 705) – underscores the importance of the topic while adding cross-disciplinary complexity. Modularity receives the most attention within two literature bodies, namely the operations management respectively the management science literature, and contributions within the field of design theory and engineering management (Salvador et al., 2002). Within the field of management accounting, modularity is less prominently discussed and mainly characterized by studies on target costing (Wouters and Morales, 2014).

This study critically examines how the strategic implementation of modularity in manufacturing companies influences their overall competitive capabilities, assuming the need for tradeoffs during new product development (NPD). Modularity in product design and component commonality are major corporate decisions related to product architecture (Wouters et al., 2011). A company’s product architecture and related decisions greatly impact the company’s success, affecting the company as a whole, its products, and its image with the customer (Yassine and Wissmann, 2007). Decisions on product architecture thus impact all competitive capabilities.

Within the literature on competitive capabilities, there exist two prevailing streams of view, namely the synergistic and the tradeoff perspective. Recently, a third somewhat integrated perspective has emerged (Nand et al., 2024). The synergistic school argues that competitive capabilities can be optimized simultaneously (Jayaram and Narasimhan, 2007). For instance, Ittner and Larcker (1997) find a link between reducing lead time and increasing product quality, as the reduced overall time increases the pressure to work efficiently. The tradeoff school, however, holds that due to limited resources and fierce competition, decision-makers must set clear priorities because corporate key performance indicators cannot all be optimized simultaneously. This view is dominant in the literature, supported by more contributions and stronger empirical evidence (Boyer and Lewis, 2009; Van Oorschot et al., 2011). According to this perspective, competitive capabilities – once optimized – always benefit at the expense of one another, i.e. optimizing costs at the expense of quality (Jayaram and Narasimhan, 2007).

Our review adopts the tradeoff perspective and highlights the financial tradeoffs during the development of new products. Rather than treating product architecture as exogenous to these tradeoffs, we examine how architecture decisions – particularly the choice of a modular design – reposition the tradeoffs that decision-makers face. Modularity does not eliminate the need for tradeoffs but changes where they occur and how severely they bind. Generally speaking, tradeoffs appear once project goals cannot be attained simultaneously and an “either-or” decision respectively a preference order is required (Renzi et al., 2017). During the process of developing new products, decision-makers try to achieve a multitude of targets and thereby need to answer a large amount of product architecture-related questions. Financial tradeoffs during NPD are the central topic within this chapter and the entire dissertation. Consequently, we implicitly adopt a tradeoff perspective concerning competitive capabilities, i.e. “a company’s actual competitive performance in the marketplace” (Lau et al., 2009, p. 307), in our research agenda. Drawing on Smith and Reinertsen's (1995) identification of four financial objectives in NPD management – project timeliness, product performance, development expense, and product cost – and Krishnan and Ulrich's (2001) observation that these goals inherently involve tradeoffs, we conceive financial tradeoffs during NPD as situations in which a minimum of two financially relevant project objectives cannot be optimized simultaneously. This conflicting situation requires decision makers to prioritize among competing cost, time, and quality targets following the ideal of an overall profit maximization. Consequently, we raise the following research questions to be answered by this integrative literature review.

RQ_1: "What financial tradeoffs arise around the development of new interdependent products?"

RQ_2: "What is the impact of product architecture decisions on these financial tradeoffs?"

The remainder of this paper is organized as follows. The next section presents the three operations management theories on competitive capabilities that underpin our research perspective. Section 2.3 presents the research method of an integrative literature review. Section 2.4 provides the central definitions and technical terms used throughout the contribution. In section 2.5, the results section of this literature review, we present a detailed discussion of tradeoffs on the product and project levels retrieved from the reviewed literature, reflect on the impact of modularity, and condense the findings in our conceptual framework before section 2.6 ultimately concludes the paper.

2.2 Operations Management Theories concerning Competitive Capabilities

As mentioned in the introduction, operations management literature distinguishes three streams concerning the interrelationships of competitive capabilities and the required approaches for decision-making. This section provides some background information on each of these three literature streams – tradeoff, synergy, integration – for a better understanding of the overall adopted research perspective on competitive capabilities.

Tradeoff School

The idea that certain competitive capabilities may be mutually exclusive or at least pose diverging requirements was first famously addressed by Skinner (1969), who acknowledged the need for clear prioritization of competitive capabilities aligned with an overall company strategy (Boyer and Lewis, 2009). Delegating operational decisions to technical experts without a clear strategic agenda likely leads to inefficiencies, since tradeoffs among the "variables of cost, time, quality, technological constraints, and customer satisfaction" (Skinner, 1969, p. 140) arise and cannot all be fulfilled at the highest level.

A few years later, Skinner (1974) re-emphasized the need to make tradeoffs through his theory of the focused factory. A factory cannot – and is not obliged to – perform equally well in every performance-relevant aspect. The aspiration of fulfilling all performance categories at the highest level is unrealistic given limited resources. Moreover, many corporate brand-positioning strategies that focus on selected capabilities secure a viable market share once well executed (Skinner, 1974). Porter (1996) extended this logic to business strategy more broadly: making the right tradeoffs is fundamental to strategy, as a well-executed strategy allows companies to preserve a competitive advantage through a unique value proposition and avoid the pitfall of being left without a clear marketable difference.

Synergy School

First skepticism of the tradeoff view was formulated by Nakane (1986) who analyzed Japanese companies and found that it may not be possible to fully exploit one capability at the expense of another, because basic quality levels must necessarily be fulfilled. For instance, fully minimizing costs at the expense of product quality may generate additional costs in the form of warranty expenses. A pure optimization of just one capability may thus result in organizational chaos (De Meyer et al., 1989).

Based on these insights, Ferdows and De Meyer (1990) published their famous *sand cone model* that established the cumulative respectively synergistic view on competitive capabilities as an alternative to the tradeoff perspective. The model conceptualizes the optimization of competitive capabilities as building a cone out of sand, where different layers correspond to different competitive capabilities and the sand represents managerial effort or resources. The model assumes four competitive capabilities in descending order of importance, namely quality, dependability, speed, and cost-effectiveness. To build a stable cone, a company must first allocate resources to the most important capability (quality). When the company subsequently invests in the next layer (dependability), any resources allocated there automatically strengthen the underlying layers. While the sand cone model illustrates the idea behind simultaneously optimizing multiple capabilities, it implies that moving up the layers requires exponentially growing effort, making simultaneous optimization challenging – yet not impossible (Ferdows and De Meyer, 1990). Accordingly, “to improve the cost-effectiveness by 10%, it will be necessary to improve the speed by a larger percentage, say 15, dependability by yet a larger percentage, say 25, and quality by still larger, say 40%” (Ferdows and De Meyer, 1990, p. 174).

Rosenzweig and Roth (2004) extend the sand cone model by combining it with the competitive progression theory (Nand et al., 2024). That implies that the actual order within which the company tries to mutually optimize its capabilities determines whether these are compatible or incompatible with each other (Rosenzweig and Roth, 2004).

Integrated School

The integrated theory emerged to reconcile the two preceding schools (Boyer and Lewis, 2009). It seeks complementarities between the tradeoff and synergy perspectives to bring them closer together and ultimately unify them (Nand et al., 2024). The first prominent approach was the theory of performance frontiers published by Schmenner and Swink (1998) which established the foundation of the integrated school. Accordingly, a performance frontier describes the highest achievable level of performance (Schmenner and Swink, 1998). The authors distinguish between the theoretically highest achievable performance level, influenced by long-term strategic choices, and the realistically highest achievable performance level, steered by short-term operational choices (Rosenzweig and Easton, 2010). They refer to the former performance frontier as an “asset frontier” and to the latter as an “operating frontier” (Schmenner and Swink, 1998, p. 108).

This distinction is central to unifying the tradeoff and synergistic perspectives. As long as a company performs below its operating frontier, it can improve on multiple dimensions simultaneously, because operational slack likely reveals inefficiencies. However, once a company aims at optimization beyond the operating frontier to reach its asset frontier, tradeoffs become mostly inevitable (Rosenzweig and Easton, 2010).

Table 1 summarizes the three schools.

Table 1 – Overview of the Operations Management Theories concerning Competitive Capabilities

	Tradeoff School	**Synergy School**	**Integrated School**
Competitive Capabilities	*A "company's ability to create products with certain competitive performance, which can win orders from its competitors"* (Lau et al., 2009, p. 307)		
Central Claim	Competitive capabilities can only be optimized at the expense of one another.	Competitive capabilities can aid one another which allows their synergistic optimization.	Reconcile differences between the Tradeoff and Synergy School.
Relationship between Competitive Capabilities	Mutually exclusive.	Mutually reinforcing / Complementary	Mutually reinforcing up to a certain point, then mutually exclusive.
Cornerstone Paper	Skinner (1969)	Ferdows and De Meyer (1990)	Schmenner and Swink (1998)

2.3 Research Method

We chose an integrative literature review as the most appropriate research method for this contribution. Therefore, we follow the checklist by Torraco (2005) that considers three stages – preparing, organizing, and writing an integrative literature review – and provides some guiding questions tailored to each stage. For a better understanding, we depict the checklist by Torraco (2005) in Figure 2.

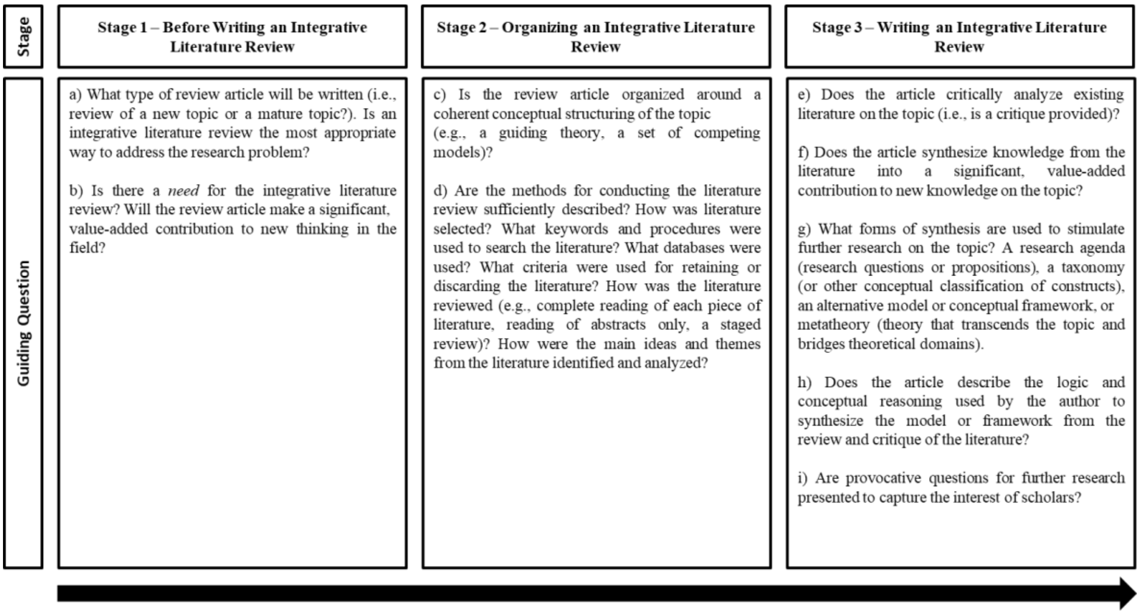

Figure 2 – Checklist for Writing an Integrative Literature Review, based on Torraco (2005, p. 365)

Stage 1 – Before Writing an Integrative Literature Review

We begin with Torraco's (2005) first set of guiding questions, which concern the rationale for choosing an integrative review and the added value of the contribution. According to Snyder

(2019), there exist three prominent types of literature reviews – systematic, semi-systematic, and integrative – within management research. Systematic reviews demand strict requirements concerning search strategy and article selection and are most applicable for quantitative analysis of narrow research fields. Semi-systematic reviews are suited for analyzing broad topics that have developed across diverse disciplines; they typically contrast opposed viewpoints to identify research gaps, diverging conceptualizations, and the general development over time. Integrative reviews use a creative collection of data to capture diverse perspectives on a research field. Rather than aiming to collect all published articles on a subject, integrative reviews combine multiple perspectives to create new taxonomies, classifications, theoretical models, or frameworks (Snyder, 2019).

The underlying topics of product design, financial tradeoffs, cost management, and product development are all mature with first studies dating back to the 1960s (Frandsen, 2017). Therefore, we do neither aim at providing an exhaustive collection of published evidence within the field (systematic review) nor at providing a temporal or context-based review of published literature in different scientific fields (semi-systematic review). Rather, we aim at synthesizing existing research findings into a conceptual framework[1] that clearly illustrates existing financial tradeoffs during NPD as well as the role of product architecture in relieving these tradeoffs (integrative review).

Table 2 provides a comprehensive summary of literature reviews that we are aware of at the intersection of product design, financial tradeoffs, cost management, and product development published after the year 2000.

Table 2 – Summary of Existing Literature Reviews

Source	Content (High Level)
Da Silveira et al. (2001)	Da Silveira et al. (2001) review the literature of mass customization that characterizes a follow-up development of a successful application of modular product design. Accordingly, one of the crucial success factors of mass customization is that the products are easily customizable which cannot be exclusively yet efficiently achieved by having a modularly designed architecture.
Krishnan and Ulrich (2001)	Krishnan and Ulrich (2001) examine the development process of new products and place central emphasis on questions that are raised during as well as in the setup of new product development projects. Their review summarizes evidence from multiple streams of research such as marketing, operations management, and engineering design. Structurally the authors split the development process into four subcategories, namely concept development, supply chain design, product design, and production ramp-up and launch. The review focuses on the internal decision-making challenges within a firm.
Ramdas (2003)	Ramdas (2003) reviews product variety decisions that determine the portfolio of the company and, through their impact on the cost and revenue side, the profitability of the company. Accordingly, variety is created by decisions upon the dimensions of variety, the product architecture, the degree of customizability, and timing. Once these aspects are clarified, variety implementation strategies concern internal processes and the supply chain answers issues of process capabilities, points of variegation, and day-to-day decisions.
Gershenson et al. (2004, 2003)	Gershenson et al. (2004, 2003) provide two literature reviews whereof the earlier one collects knowledge on the definitions and benefits of having a modularly designed product portfolio and the later one summarizes measures and design methods to achieve modularity. Accordingly, there exists consensus on the independence of functional requirements in modularly designed products whose cost benefits stem significantly from learning curves and reduced part costs (Gershenson et al., 2003). Modularity may be achieved by grouping similar components into modules and iteratively checking different design solutions (Gershenson et al., 2004).
Labro (2004)	Labro (2004) employs an activity-based costing approach to review the cost-driver and cost-level effects of component commonality published in the operations management research literature from a management accounting point of view. The effects are analyzed within a five-level hierarchy (Unit, Batch, Order, Component, Supplier level) through an activity-based framework. The study illustrates that within and between the

[1] A conceptual framework as such "relates concepts, empirical research, and relevant theories to advance and systematize knowledge about related concepts or issues" (Rocco and Plakhotnik, 2009, p. 128).

	level of analysis cost effects of component commonality may be opposite and that general statements such as the use of common components possessing a positive influence on the cost structure must be viewed with caution.
Simpson (2004)	Simpson (2004) emphasizes the pressure on companies to offer customizable products to the markets. He argues that product platforms and modular product design are key strategies to create product families efficiently. A special emphasis is put on platform leveraging strategies, platform metrics, and product family optimization. The latter often considers the tradeoff between maximizing demand by product performance and minimizing costs by increased commonality.
Jose and Tollenaere (2005)	Jose and Tollenaere (2005) summarize knowledge of product standardization, product modularization, and the use of product platforms. It discusses the tradeoff between product standardization and differentiation and illustrates the influence of modularization and product platform thereupon.
Fixson (2007)	Fixson (2007) analyzes the effects of modularity and commonality within four categories, i.e. product performance and quality, product variety, product costs, and time. Following this categorization, Fixson (2007, p. 92) stresses that the "results of modularity's effects on cost are mixed" and that effects like economies of scale and costs of complexity need to be balanced against each other.
Gupta and Okudan (2007)	Gupta and Okudan (2007) highlight benefits, drawbacks, and expectations of modular product design. Thereby, they are acknowledging a gap between the industrial implementation of modularity and the scientific evidence-based understanding of its effects.
Jiao et al. (2007)	Jiao et al. (2007) provide a decision framework that builds on five consecutively aligned domains, i.e. the customer, functional, physical, process, and logistics domain. Herein, the relative left domain, e.g. the customer domain, emphasizes the desired goal to be achieved, and the relative right domain, e.g. the functional domain, clarifies how the requirements from the left domain should be satisfied.
Salvador (2007)	Salvador (2007) reviews the engineering and management literature on product modularity and finds anything but a common definition. Accordingly, his research condenses several definitional perspectives and finds that modularity is about component commonality and combinability, function binding, interface standardization, and loose coupling.
Kong et al. (2009)	Kong et al. (2009) outline the role of modular product design as a means to realize product platforms, product families, and mass customization strategies. They mention the dissent that although cost-saving potentials are among the most prominent reasons for modular product development, there is a lack of concrete evidence supporting this claim. Based on their research they develop a framework for modular product development suggesting how to map functions to components efficiently.
Bask et al. (2010)	Bask et al. (2010) categorize the identified literature into four groups, namely product, production, organization, and service-related contributions on modularity. The authors provide a detailed review of modularity-related implications in the service context.
Campagnolo and Camuffo (2010)	Campagnolo and Camuffo (2010) review management studies on modularity and cluster the identified literature into three categories according to the unit of analysis covered in the reviewed studies, i.e. studies on product design, studies on production systems and studies on the influence of modularity on organizations.
Starr (2010)	Starr (2010) provides a conceptual paper that is intended as an update to his original article of 1965 published in the Harvard Business Review (Starr, 1965). In his new contribution, he reviews the literature on modular production and finds that it is still a splintered yet often successfully applied approach that even allows for cost reductions, partly at the expense of quality.
Wazed et al. (2010)	Wazed et al. (2010) summarize the literature on commonality in a broad sense including other literature reviews, mathematical models, and knowledge of commonality indices. The authors argue that all forms of commonality measurement are designed to identify the right share of commonality to resolve the tradeoff between a lack of distinctiveness and a too-high total cost level.
Fogliatto et al. (2012)	Fogliatto et al. (2012) provide an updated version of their mass customization review that was published a decade ago by Da Silveira et al. (2001). Herein they reconfirm the customizability of products as a success factor for mass customization and find that modular design as well as product platforms work as enablers for this success factor.
Gawer and Cusumano (2014)	Gawer and Cusumano (2014) review literature with a focus on industry applications of product platforms. Thereby they identify two dominant platform types, i.e. internal company or product specific platforms and external industry specific platforms.
Pirmoradi et al. (2014)	Pirmoradi et al. (2014) extend the review of Jiao et al. (2007) and focus on approaches for product family design to resolve the tradeoff between cost-effectiveness and product variety to satisfy market demands. They emphasize the development of product platforms as a means to minimize this tradeoff. Within their review, the authors consider customer involvement during development, market-driven studies, metrics on assessing product platforms, product platform optimization, and issues concerning platform development and design.
Wouters and Morales (2014)	Wouters and Morales (2014) review cost management during NPD in management accounting journals. The authors find that the cost management method of target costing has received the highest attention in the reviewed contributions followed by modular design and common components. The latter serve as parts of the management accountant's toolset once the cost management activity concerns total costs for a portfolio of products or services. Within their subsections on component commonality, and modular design the tradeoffs related to development and direct costs are discussed.
Harland and Yörür (2015)	Harland and Yörür (2015) identify 21 decisions made during product platform development projects (PPDP). They group these decisions into the categories of market-related and synergy-related decisions, whereof the former category is deemed to increase a company's competitive advantage and the latter one is oriented on potential cost reduction opportunities for the applying company. From a management accounting perspective, a reduced cost position itself embodies a competitive advantage, which is why we understand the differentiation between the identified categories of PPDP decisions in either decisions with or without a direct market

	relation. The latter category encompasses decisions among tradeoffs such as choosing between development costs, production costs, and platform performance.
Zhang (2015)	Zhang (2015) summarizes the knowledge of product platform development and related new derivates such as flexible platforms. The author refers to the potential benefits of product platforms in dealing with the tradeoff in product performance and manufacturing costs.
Bonvoisin et al. (2016)	Bonvoisin et al. (2016) review the literature on modular product design and identify three groups of activities, i.e. design with modules, identification of modules, and design of modules. The authors create a modularization concept map that links drivers, principles, and metrics of modular product design.
Facin et al. (2016)	Facin et al. (2016) combine a systematic literature review with a bibliometric analysis and investigates the contributions concerning product platform development. The results stress that the platform concept requires clear and strategic management and acknowledge that product platforms are not an ultima ratio for developing successful product families.
Ma and Kremer (2016)	Ma and Kremer (2016) use a slightly different approach to review the literature on modularity as they employ a conceptual framework covering sustainability with the dimensions of economic growth, social progress, and environmental stewardship. Within the dimension of economic growth, they discuss and summarize cost aspects of modularity considering supply chain costs, product development costs, and production costs.
Wouters et al. (2016)	Wouters et al. (2016) extend their previous review of Wouters and Morales (2014) by focusing on a new stream of research. Whilst Wouters and Morales (2014) reviewed cost management methods during NPD in the management accounting (MA) literature, Wouters et al. (2016) review the innovation and operations management (IOM) literature. In contrast to the MA literature, the IOM literature examines modular design rather simulation-based than as qualitative studies. Within their section on modular design, tradeoffs concerning direct and overhead costs are discussed and a tradeoff framework for the development process is presented.
Frandsen (2017)	Frandsen (2017) uses a bibliometric analysis to review the modularity literature within the operations research, management, and business economics literature. He illustrates the development of the literature on modularity between 1990 to 2015, identifies key areas of interest, e.g. economics of substitution, and postulates eight areas for further research, i.e. service modularity, optimizing design of complex systems, reconfiguration and dynamic capabilities, vertical integration/disintegration, effects of modularity on organizations and supply chains, open innovation, case-based research, and developing across boundaries.
Renzi et al. (2017)	Renzi et al. (2017) review decision-making approaches and find that despite their proven effectiveness, many decision-makers prefer testing and expert-based judgment. While the review neither directly considers specific tradeoffs nor the product architecture, it summarizes approaches to decision-making that can be used during product development to solve conflicting issues.
Ripperda and Krause (2017)	Ripperda and Krause (2017) provide a literature review that clarifies the knowledge of the cost effects of product variety and modular product family structures. The authors present a new approach to predict, assess, and reduce these cost effects during product development. Their process consists of three steps, i.e. cost prognosis, cost assessment, and cost reduction. Accordingly, the authors collect evidence on the cost effects of variety and modularity and henceforth outline how design decisions affect the total costs of the product.
Wouters and Stadtherr (2017)	Wouters and Stadtherr (2017) extend the contribution of Labro (2004) and review modularity as a strategy for cost management. They provide a detailed review of the cost implications of modularity using the example of a product lifecycle starting with the initial product design and ending with its disposal.
Rennpferdt et al. (2019)	Rennpferdt et al. (2019) summarize the literature concerning modular product architecture of product-service systems. The authors summarize nine methods for the development of product service systems, i.e. life-cycle oriented design, modularization based design, modular development of product service systems, module partition process model, collaborative development, service modules, module division, and customization-oriented design.
Hackl et al. (2020)	Hackl et al. (2020) use a lifecycle perspective to review the literature on modularity effects on a company's economics across different lifecycle phases starting at product development and ending at product production. The authors contribute a literature-based network model that illustrates the effects of modularity, e.g. an increased use of common components, on the lifecycle, e.g. a reduced variety of single components, and its impact on the company's economic performance, e.g. the development costs per unit.
Han et al. (2020)	Han et al. (2020) map platform development approaches to tradeoffs. A modular product platform resolves the tradeoff between diversity and costs, a scalable product platform reduces the tradeoff between product performance and costs, an uncertainty-oriented product platform helps to cope with uncertainty during the development process.
Shamsuzzoha et al. (2020)	Shamsuzzoha et al. (2020) collect evidence concerning internal, external, and interfacial complexity and the respective role of product architecture. The authors emphasize the strategic role of the architecture decision and its beneficial impact on the company's total cost.
Windheim (2020)	Windheim (2020) reviews the literature on product family design and collects evidence concerning modular product design, its effects on the product structure from a lifecycle perspective, as well as methods to assess product structures as such.
Gauss et al. (2021)	Gauss et al. (2021) identify module-based product family design as corporate solution to the tradeoff of having high external product variety without paying for it by reduced production efficiency. The authors review the literature in order to provide a structured approach for module-based product family design consisting of three steps, i.e. constructing a functional model, suggesting structured models, and proposing a construction heuristic.
Mertens et al. (2022, 2021)	Mertens et al. (2022, 2021) conduct a bibliometric analysis on modularization to analyze the development streams within this topic and identify current as well as future trends. The findings suggest that the aspects of cost-efficacy and flexibility remain a highly researched topic within modularity that gets extended by considerations concerning sustainability, innovation, and digitalization.

Magnacca and Giannetti (2024)	Magnacca and Giannetti (2024) review management accounting and new product development (NPD) and cluster the identified research streams into three groups, namely techniques and calculations, information types and roles, and the involvement of the management accountants in the development process. For all these three groups the authors summarize core propositions that capture the specific future research avenues. The review as such is less concerned about tradeoffs or modular design but provides a deep insight into the role of management accounting during NPD.
Monetti and Maffei (2024)	The review of Monetti and Maffei (2024) investigates several drivers of product architecture decisions, such as the motivation behind modularizing or the strategy how it is implemented. The authors stress the crucial role of the product architecture concerning a company’s costs and the performance of its products.
Roy and Abdul-Nour (2024)	Roy and Abdul-Nour (2024) provide a literature review concerning the implementation of modularity. They base their research on strategic production objectives ranging from mass production over mass customization to mass personalization. The authors argue for modularity as means once the need of mass personalization is present in the industry acknowledging the implied need for making tradeoffs related to key performance indicators.
Nørgaard et al. (2025)	Nørgaard et al. (2025) review the management accounting (MA) and innovation and operations management (IOM) literature, like Wouters and Morales (2014) on MA literature Wouters et al. (2016) on IOM literature. In contrast, the authors focus specifically on cost management techniques to capture the effects of modularity and find that cost techniques like volume-based costing, activity-based costing, time-driven activity-based costing, and target costing run short in capturing the predominantly indirect benefits of having a modular product architecture. As counteracting measure, the authors propose to assess cost effects on distinct levels of abstraction, i.e. the component, the subsystem and the product level.

Based on the analysis from the existing literature reviews, we find that they typically discuss financial tradeoffs as one out of many distinct aspects to be considered during the individual phases of a product’s lifecycle (Labro, 2004; Wouters and Stadtherr, 2017). Therefore, we find it immensely important to provide the literature with an exhaustive review that centrally analyzes financial tradeoffs during NPD to condense the dispersed set of knowledge that we found in diverse literature streams. Thereby, we add value by providing a new perspective with tradeoffs at the focal spot.

Stage 2 – Organizing an Integrative Literature Review

Second, we address Torraco’s (2005) next set of guiding questions concerning the conceptual structuring and employed methods of the review. We build our research on the guiding theory of tradeoffs, which emphasizes that product performance characteristics require clear prioritization (Boyer and Lewis, 2009). As an underlying framework, we use and expand the work of Wouters et al. (2016) illustrated in Figure 3. It shows the tradeoffs among diverging targets concerning various competitive capabilities during NPD on a product as well as on an overarching project level.

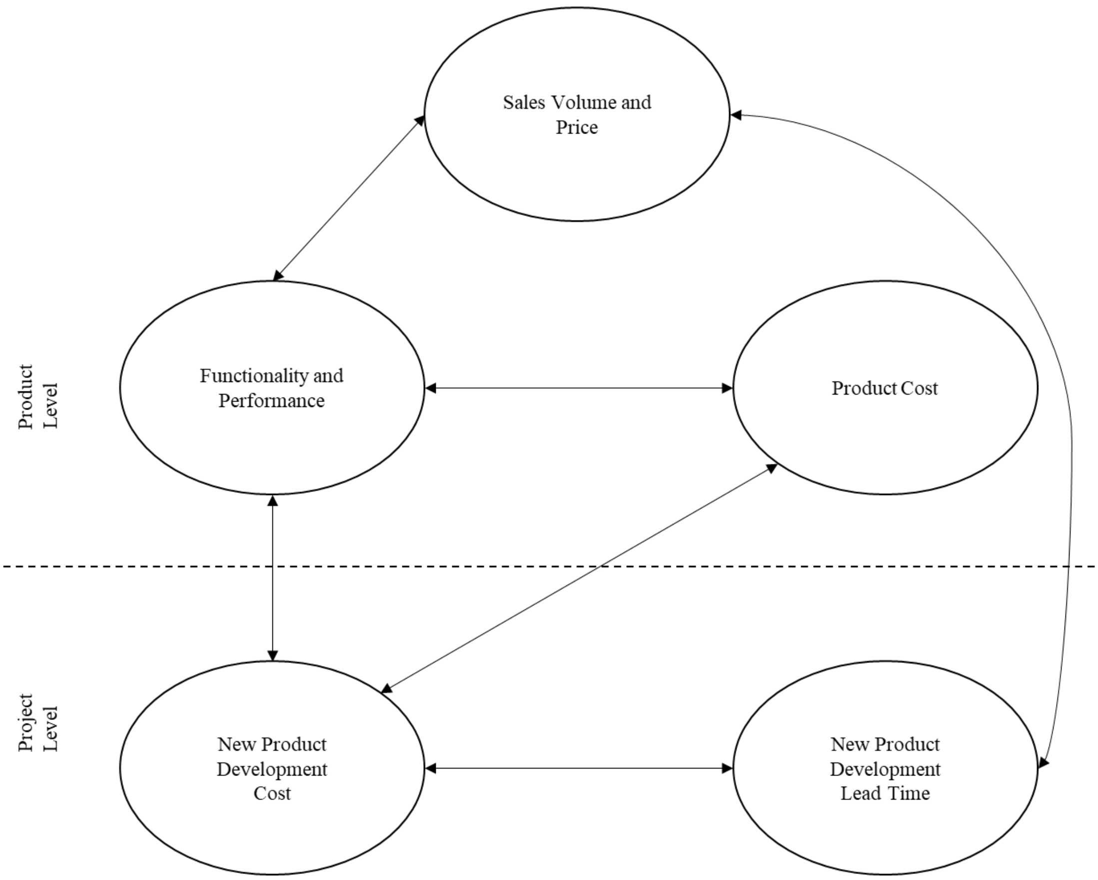

Figure 3 – Underlying Conceptual Tradeoff Framework, based on Wouters et al. (2016, p. 148)

We researched the databases Scopus, Web of Science, and Google Scholar using specific key-words covering the fields of product design, financial tradeoffs, cost management, and product development. Table 3 presents the used search strings.

Table 3 – Overview of Covered Research Fields and Exemplary Key Words

Field of Research	**Exemplary Key Words[a]**
Product Design	• Product Architecture • Component Commonality • Parts Commonality • Modularity • Integrality • Modular Product Design • Product Platforms • Product Family
Financial Tradeoffs	• Financial Tradeoffs • New Product Development Tradeoffs • Competitive Capabilities • Product Development • Decision-Making • Product Architecture Decisions
Cost Management	• Target Costing • Value Engineering • Product Benchmarking • Activity-based Costing
Product Development	• New Product Development • Fuzzy Front End

[a] Representatively understood as generalized keywords rather than exhaustive variations (e.g. “Modularity” instead of “Modular”)

Among our five most cited journals were the *Journal of Product Innovation Management*, *IEEE Transactions on Engineering Management*, *International Journal of Production Economics*, *Management Science*, and the *Journal of Engineering Design*. These highly referenced journals possess a high-quality ranking in the VHB-JOURQUAL3 – reaching a quality score between *B* and *A+* – as well as in the SCImago Journal Rank index of 2023 – belonging to the upper quantile (Q1) and half (Q2) of the best journals in their discipline[2]. Table 4 provides a brief overview on the most important journals for this review.

Table 4 – Selected Overview on the Most Cited Journals within this Literature Review

Rank	Journal Name	Total References	VHB-JOUR-QUAL3	SCImago
1	Journal of Product Innovation Management	11	A	Q1
2	IEEE Transactions on Engineering Management	8	B	Q1
3	International Journal of Production Economics	7	B	Q1
4	Management Science	7	A+	Q1
5	Journal of Engineering Design	6	not listed	Q2
…[a]	…	…	…	…

[a] Full table, i.e. “Overview on the Most Cited Journals within this Literature Review” can be found in the Appendix

In addition to our keyword search, we conducted forward as well as backward search strategies to enlarge our state of knowledge (Webster and Watson, 2002). We also manually added papers known from previous research projects, discussions with scholars and researchers in the field, and insights from seminar work and thesis supervision at the Karlsruhe Institute of Technology. All selected and cited sources passed a four-step selection process as of Lubbe et al. (2020): Step 1 – Paper identification by keyword search; Step 2 – Paper relevance check by title analysis; Step 3 – Paper analysis by abstract review; Step 4 – Paper review by critical study.

Stage 3 – Writing an Integrative Literature Review

Third, we address the remaining guiding questions of Torraco’s (2005) checklist regarding the writing of the literature review, which concern the analysis and synthesis of the studied research papers. To do so, we followed a structured approach on all papers that reached *Step 4 – Paper Review by Critical Study* in the quality assessment. First, we used the framework of Wouters et al. (2016) that is at the base for this review and mapped all thoroughly analyzed papers onto the framework. Besides, we started noting down all impacts of how the product architecture influences the identified tradeoffs. An example for such impact is over- or underspecifying a component by employing it in several products. Driven by the numerous references and the discussed tradeoffs therein, we found that the original framework of Wouters et al. (2016) is not exhaustive enough for our purposes as it lacks certain links we identified and found necessary. One such link is the tradeoff that occurs between the product related aspects of functionality and performance and the project related aspects of NPD lead time. Hence, we added an arrow per identified missing link into our conceptual framework to extend the figure of Wouters et al.

[2] While the SCImago Journal Ranking provides an exhaustive assessment of diverse journals, the VHB-JOURQUAL3 concentrates on journals relevant for Business Administration. Consequently, the Journal of Engineering Design is not included as it belongs to the field of engineering design.

(2016). Besides, we added product architecture impacts through modular product design to the model. We discuss the extended version in section 2.5.2.

2.4 Central Definitions

In this section, we discuss the theoretical background knowledge underlying this review. A collective understanding of central terms – product development process (PDP), product programs, product architecture, common components, modules, and product platforms – is crucial for the remainder of this paper, as we investigate the influence of product architecture on financial tradeoffs during NPD. Expert readers may directly proceed to section 2.5, where we present the results of this integrative literature review.

2.4.1 Product Development Process (PDP)

For a common understanding of the PDP, we employ the definition of Ulrich and Eppinger (2016, p. 12) which reads as follows.

"A product development process is the sequence of steps or activities that an enterprise employs to conceive, design, and commercialize a product."

These steps or activities are essentially an iterative coevolution of problem identification, information processing, and issue resolution that are required to overcome the obstacles in developing a new product (Gericke et al., 2021). The scientific literature and the collected best practice knowledge, provide diverse process models for the development of (new) physical as well as software-based products. Hence, there is not one universal process model that suits the needs of all industries or development projects (Li et al., 2019). Next to the process models established by scientific research, there is a considerable number of process models, like the Toyota product development method, that established their status as accepted process to develop and design new products (Tomiyama et al., 2009). Accordingly, classification schemes are a popular strategy to distinguish among the individual available models. Tomiyama et al. (2009) provide a two by two matrix to categorize design theory and methodology based on whether they are described abstractly or concrete and generally or individually. Wynn and Clarkson (2005) distinguish among three classification schemes, i.e. stage vs. action-based models, problem vs. solution-oriented literature, and abstract vs. analytical vs. procedural approaches to describe the product design process. Even within an organization, the employed product development processes may be different due to the diverse types of development projects (Ulrich and Eppinger, 2016). Yin and Zhang (2021) provide an overview of seven common NPD process models, Porananond and Thawesaengskulthai (2014) list nine such models. Otto et al. (2016) provide a flow chart model dedicated to the development process of new products that explicitly considers product architecture decision as central aspect.

Independent from the exact process model, we want to stress two important aspects once it comes to PDP models. First, despite its vast amount of distinct models, a PDP typically follows well-defined phases (Gopalakrishnan et al., 2015). These phases, whilst varying in their exact names, can be divided into a phase of *concept development*, a phase of actual *product development*, and a phase of *production* (Chase, 2001). During the phase of *concept development* several alternatives of product concepts are generated, compared among each other, and evaluated. As a unit of comparison, key performance indicators are employed. These project success factors typically encompass time, cost, and quality (Pollack et al., 2018). The second phase concerns the actual development of the product and starts once the concept development and the fuzzy front end are terminated. In this phase the actual product specifications and its requirements, such as "target costs, technological performance, customer interfaces, market release dates, and organizational resources" (Davila, 2000, p. 385), are defined. Besides, the actual product development stage encompasses activities of resolving tradeoffs and transferring them into the final product (Davila, 2000). Hence, issues of material selection, production costs, and product performance are finally set in the phase of product development. Thereby, a clear product and platform concept – if applicable – is finalized (Khurana and Rosenthal, 1997). Testing activities evaluate pre-production versions of the product and use prototypes to analyze whether the built product works and how well it fulfills the given customer requirements. Once the prototypes are approved, the product is prepared for its release followed by production ramp-up (Ulrich and Eppinger, 2016). Once the production process is proven to be stable, the ramp-up phase converges into real production and complements the development process (Ulrich and Eppinger, 2016).

Second, product development can be supported from a holistic systems engineering based perspective as initially contributed by Pahl and Beitz (2007). A holistic and product generation overarching perspective is thereby essential as the development of most products (more than 80%) is realized in generations where the individual new product is rather an evolution of a predecessor product than a completely new product (Albers et al., 2016). As the modern PDPs are dynamic and interconnected new models, like the *Three-Cycle Model of Product Development* of Gausemeier et al. (2001), emerged addressing these challenges in modern product development. Besides, the *Munich Procedural Model* is a problem resolution process containing seven task elements that need to be fulfilled emphasizing flexibility and pragmatic solutions (Lindemann, 2014). Also, the *integrated Product engineering Model* of Albers and Meboldt (2007) explicitly accounts for the interaction of activities, requirements, results and methods and therefore answers dynamism of modern development projects, which are recently also covered by the *model of System Generation Engineering* (Albers and Rapp, 2022).

Figure 4 shows the generic PDP model from Ulrich and Eppinger (2016) and highlights its phase-related core activities. At the end of each phase, management holds a decision-making meeting, where the status of the project gets reviewed and decisions on its future are made (Davila, 2000).

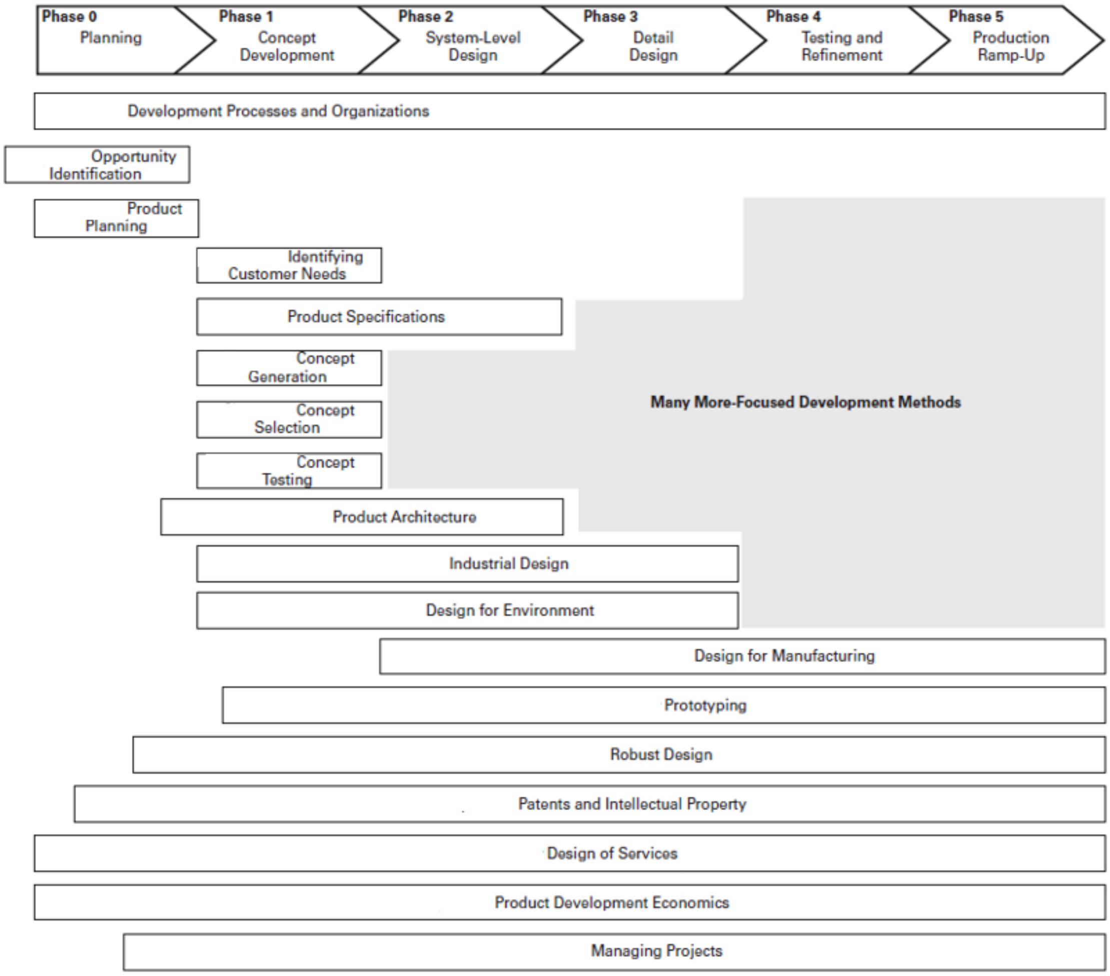

Figure 4 – The Generic Product Development Process (PDP) and its Phase-Related Core Activities, copied from Ulrich and Eppinger (2016, p. 9)

2.4.2 Product Program

Financial tradeoffs have different implications once we analyze them on a single product or overarching project level. The degree to which financial tradeoffs may be alleviated by product architecture decisions – such as developing a shared platform for multiple products or sharing components among various products – depends on the diversity and scale of a company's market offering (Gebhardt et al., 2016). The product program describes the market offering of a company on its highest aggregated level. For a common understanding, we use the definition of Krause and Gebhardt (2023a, p. 62).

"The product program is the totality of the products offered by a company."

The product program summarizes the production program as well as other services, like financial services, offered by the company. From an engineering perspective on NPD, the production program, i.e. the totality of the company's manufactured products, is of interest on the next more granular sublevel. For the definition, we again refer to Krause and Gebhardt (2023a, p. 62).

"The production program describes the purchased products, which are offered on the market as merchandise without substantial changes, and services."

A company's production program can be further broken down into product lines, product families, and ultimately product variants. We adopt the clustering from Krause and Gebhardt (2023a), where a product line represents a group of product families from an organizational point of view. In some other contributions, however, the terms product line and product family are used interchangeably (Jiao et al., 2007) or distinguish product lines as term of a rather marketing and sales related context, e.g. to advertise products to a customer, and product families as rather engineering-focused describing technologies and core technical parts (Jonas, 2013; Laschka, 2021). As stated, we adopt the definition of Krause and Gebhardt (2023a, pp. 62–63), which reads as follows.

"The product line represents a set of products as a subset of the product program which have similar application areas, functions or production processes and whose combination into a product line makes sense from a business and organizational perspective. Product lines represent groups of product families from an organizational point of view. (...) A product family refers to a set of product variants that have similar functional principles, technologies and the same areas of application or production processes."

Product families contain product variants, which form a lower hierarchical level. A product variant fulfills the same main functionalities as comparable variants of the same product family but differ in at least one property, which typically affects a customer's buying decision, from all other product variants within a product family (Krause and Gebhardt, 2018). Hence, a product family targets a whole market segment and a product variant specifically focuses on a subset of the requirements within the segment (Jiao et al., 2007). As definition, we refer to Krause and Gebhardt (2023a, p. 63) which reads as follows.

"Product variants are products with very similar form and/or function and usually a high proportion of identical groups or parts. They are technical systems with the same purpose, which have the same basic functionality but differ in at least one characteristic."

Figure 5 illustrates a schematic example of a product program.

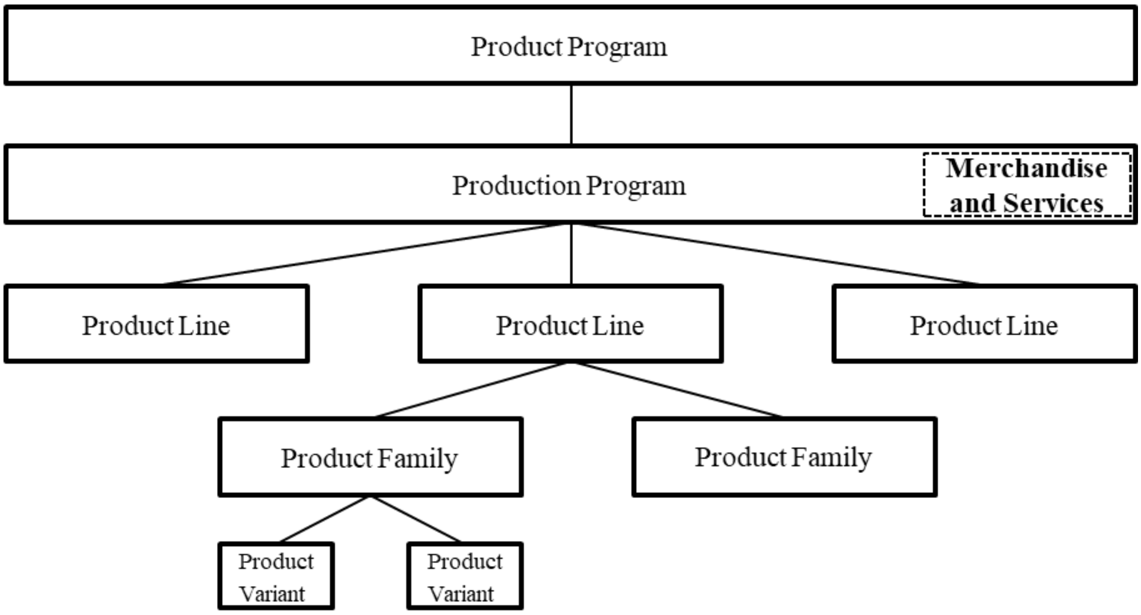

Figure 5 – Example Product Program, based on Krause and Gebhardt (2023a, p. 62)

Besides, a company's market offering can also be assessed over time. Analyzing a product over time, we use the terms product version and product generation. A product version describes the state of a certain product within its product lifecycle. Such a product lifecycle is industry-specific and can generally be divided over time into the phases of product development, product introduction, growth and maturity, saturation, and decline (Feldhusen et al., 2013b). Typically, a product generation encompasses different product versions until it is replaced by its succeeding product generation. As stated above, most new products are essentially not a completely new greenfield product but rather a new product generation (Albers et al., 2016). Within the automotive industry, a given product variant is first refined as a facelift version of the original product until it gets replaced by the succeeding and hence, renewed and differentiated, product generation. Such differentiation features may be illustrated by employing the example of the Porsche 911, which used a new turbine geometry in its product generation of type 997 (Albers et al., 2015).

2.4.3 Product Architecture

We adopt the definition of Ulrich (1995, p. 419), who defines a product architecture as follows.

"Product architecture is the scheme by which the function of a product is allocated to physical components."

This definition implies two perspectives – a functional and a physical one – on structuring a product. A product architecture thus combines the structure of a product's functions and its physical layout and defines the relationship between these two (Feldhusen et al., 2013a). Similarly, Sanchez (2002) clarifies that a product architecture refers to a product's functional components as well as the intended way these functional components should interact.

A function responds to customer requirements and describes the “operations and transformations that contribute to the overall performance of the product” (Ulrich and Eppinger, 2016, p. 186). In informal terms, a product function describes what the product actually does – e.g. a function of an automotive door is to provide access to the interior of the car (Feldhusen et al., 2013a; Schmidt et al., 2016). A function is solution-neutral, allowing the decision-maker to explore different alternatives when defining the product architecture (Schuh and Riesener, 2017). All functions defining the product collectively are referred to as the function structure. Within this structure, different hierarchy levels either describe the product’s overall functions at a granular level or specify them at a sub-functions level of detail (Schmidt et al., 2016; Ulrich, 1995). Typically, no more than three hierarchy levels are used, since additional levels may create confusion and increase the complexity of allocating functions to physical components (Feldhusen et al., 2013a).

The physical view of a product shows its hierarchical structure of individual components and modules. These physical parts embody the product’s functions (Ulrich and Eppinger, 2016). The product structure is an important parameter in efficiently configuring product variants, which are similar products that differentiate from each other by single properties (Krause and Gebhardt, 2018).

The functional and physical structure combined form the product architecture. Product functionalities are allocated to physical parts in “one-to-one, many-to-one or one-to-many” (Ulrich, 1995, p. 421) relationships. The allocation of functions to the components answers the question of which parts of a product will ultimately fulfill which functions (Schuh and Riesener, 2017). Figure 6 visualizes the two perspectives on product architecture.

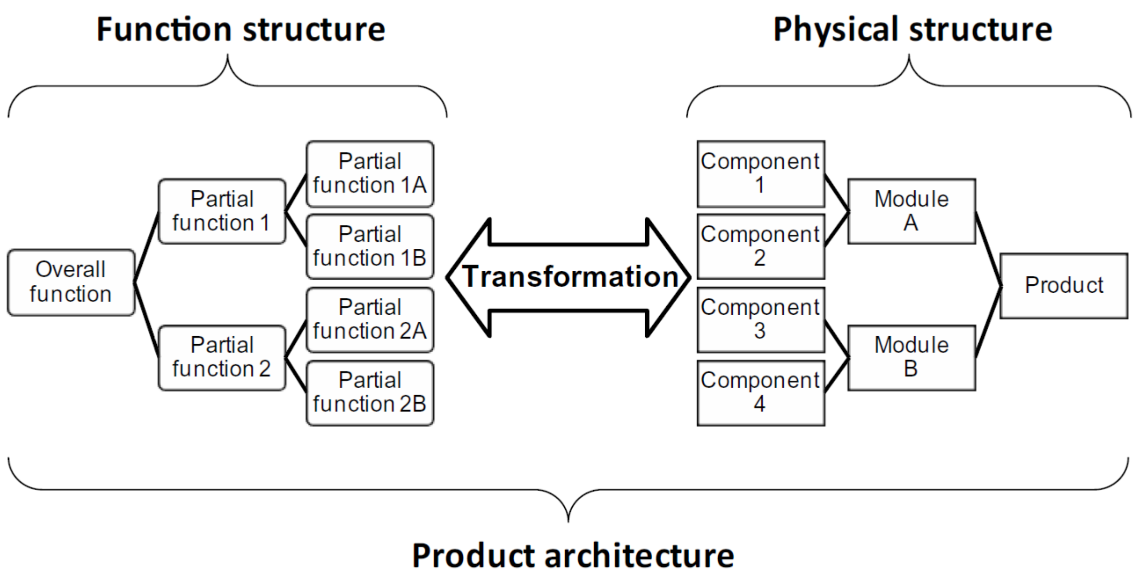

Figure 6 – Clarification of the Term Product Architecture, copied from Skirde et al. (2016, pp. 1650017–3)

The most prominent typologies of product architectures are the modular and the integral one.

Modular and Integral Product Architecture

According to Ulrich (1995, p. 422), a “modular architecture includes a one-to-one mapping from functional elements in the function structure to the physical components of the product, and specifies de-coupled interfaces between components”. The opposite constitutes an integral architecture, which allocates a product’s functions on a non-one-to-one basis to its components, with coupled interfaces between them (Ulrich, 1995). Table 5 collects key aspects differentiating modular from integral product architectures.

Table 5 – Comparison of a Fully Modular and Fully Integral Product Architecture

Criteria	Fully Modular Product	Fully Integral Product	Ref.[a]
Design Criteria	Commonality Sharing	Maximum Performance	(3)
Mapping of functions to components	One-to-one mapping with clear component boundaries	One-to-many mapping resulting in function sharing and blurred component boundaries	(1) (3)
Interfaces	Decoupled	Coupled	(1) (3)
Functional Change	Independent change of the component fulfilling the function, without required modifications to the architecture.	Any functional change yields an exchange of all components, modifications to the product architecture are required.	(1) (3)
Product Variety	A reduced number of components enables variety by mixing and matching building blocks to enable strategies of postponement.	Requires as many types of each component as there are desired combinations of functional elements to be implemented.	(1) (3)
Nature of Components	Standardized/generic with a low degree of synergistic specificity[b].	Unique/dedicated with a high degree of synergistic specificity.	(3)
Component Interaction	Well-defined and generally fundamental to the primary function of the product.	Ill-defined and may be incidental to the primary function of the product.	(4)
Component Outsourcing	Easy, due to standardized interfaces and clear function-component mapping.	Difficult, due to coupled interfaces and one-to-many function-component mapping.	(3)
Learning	Localized/Dispersed and component-specific	Interactive and product-specific	(3)
Component Substitutability and Recombinability	High, due to standardized interfaces and clear function-component mapping.	Low, due to coupled interfaces and one-to-many function-component mapping.	(3)
Optimization of performance characteristics	Local fine-tuning of specific modules and autonomous nature of innovation.	Global optimization of the entire product and systemic innovation.	(1) (3)
Management of product development activities	Loosely coordinated independent development activities. Parallelized Processes.	Highly coordinated and tight collaboration. Sequential Processes.	(2) (5)
Product Performance	Performance can only be optimized to a certain degree.	Performance can be optimized to its maximum.	(4)
Structure of the organization	Decentralized	Integrated	(2)
System Design Strategy	Decomposition	Integration	(3)

[a] Based on insights from (1) Ulrich (1995); (2) Ülkü and Schmidt (2011); (3) Mikkola (2006); (4) Huang (2000); (5) Jose and Tollenaere (2005). [b] Schilling (2000, p. 316) describes synergistic specificity as the “degree to which a system achieves greater functionality by its components being specific to one another”.

Göpfert (2009) developed a classification scheme to distinguish between integral and modular product architectures. The author employs a two-by-two matrix with physical autonomy on the x-axis and functional autonomy on the y-axis. High physical autonomy refers to easily separable and combinable singular parts. High functional autonomy means a component is mapped directly, in a one-to-one relationship, to a function. Modularly designed products are grouped in the first quadrant (high functional and physical autonomy), whereas integrally designed products are characterized by low autonomy (high dependency) in the third quadrant. The function-component allocation scheme of Fixson (2005) constitutes a similar effort using two indices. One index represents “the number of components that jointly provide a function” (Fixson, 2005, p. 354) and the second one accounts for “the extent to which this set of components also contributes to other functions” (Fixson, 2005, p. 354).

These typologies of a fully modular or fully integral product architecture illustrate the theoretically possible extremes. In practice, for nearly all products, modular design plays a role to some extent. Typically, all realized products follow a mixed design of integral and modular architectures and solely vary in the degree of modularity (Hölttä-Otto and de Weck, 2007). A variety of indices exist to assess this degree. Krause and Gebhardt (2023b) present three indices to assess product variety, seven metrics for the design process of new product variants, and eight indices to evaluate modular product structures. Hölttä-Otto et al. (2012) identified 13 metrics to measure modularity and commonality, grouped into coupling-based and similarity-based metrics. These indices are among the most prominent approaches to evaluate product architecture decisions in a non-financial manner (Wouters et al., 2011). Jung and Simpson (2017) have recently proposed a new class of indices accounting for connection strength, the density of connections within and between modules, and the proximity of interactions. As an application example, Martin and Ishii (2002) illustrate how the generational variety index and the coupling index could be used to efficiently design a water cooler.

Product modularity is widely discussed within the literature of engineering and management. Nonetheless, neither a generally accepted definition of the term “module” (Wouters and Stadtherr, 2017) nor of the term “modular” exists. The terms are ambiguously used and case-specifically defined in the scientific contributions (Bonvoisin et al., 2016). Skeptical researchers have even doubted the possibility of clearly defining the term “modular” (Göpfert, 2009). Salvador (2007, p. 219) found 40 different definitions of the construct “product modularity” in just 100 different scientific publications. This “definitional ambiguity” (Salvador, 2007, p. 219) motivated his research to summarize the given definitions and group them among five definitional perspectives: component commonality, component combinability, function binding, interface standardization, and loose coupling (Salvador, 2007). Early studies refer to modular products as products that share a given set of components within a certain line of products. Studies adopting the perspective of component commonality understand a module as either a kit of shared components across existing product variants or as a part or subassembly. The basic idea is to reduce overall manufacturing costs by using the same parts across different variants. Component combinability implies that a limited number of components is employed to create several different configurations, forming a high number of differentiated products from a limited set (Salvador, 2007). This perspective, which Baldwin and Clark (1997, p. 86) call “modularity in use”, is a prominent definitional perspective since modular product architectures have “been designed to allow the “mixing and matching” of different “plug-and-play” component variations in the overall product design to configure product variations” (Sanchez, 2002, p. 9). The third definitional perspective, function binding, indicates that a given component of a modular product performs a distinct function exclusively. Hence, within a modular product architecture function sharing, which “is the simultaneous implementation of several functions by a single structural element” (Ulrich and Seering, 1990, p. 223), is not employed. Such modular product architecture offers the advantage that the exchange of single modules (each performing a given function) easily enables the manufacturer to create new variants since the new modules perform their own unique functions (Krause et al., 2018). The fourth dimension, standardized interfaces, is a prerequisite for commonality and combinability, as otherwise an easy mix-and-match exchange of modules would not be possible (Garud and Kumaraswamy, 1993). The last perspective, loose coupling, views the product architecture as a complex system that can be broken down into smaller subsystems, or modules. Components within a module "are powerfully connected among themselves and relatively weakly connected"(Baldwin and Clark, 2000, p. 63), i.e. loosely coupled, to other modules. The interactions between modules are thus minimal, while interactions within modules may be high (Jiao et al., 2007). Figure 7 summarizes the five definitional perspectives of Salvador (2007).

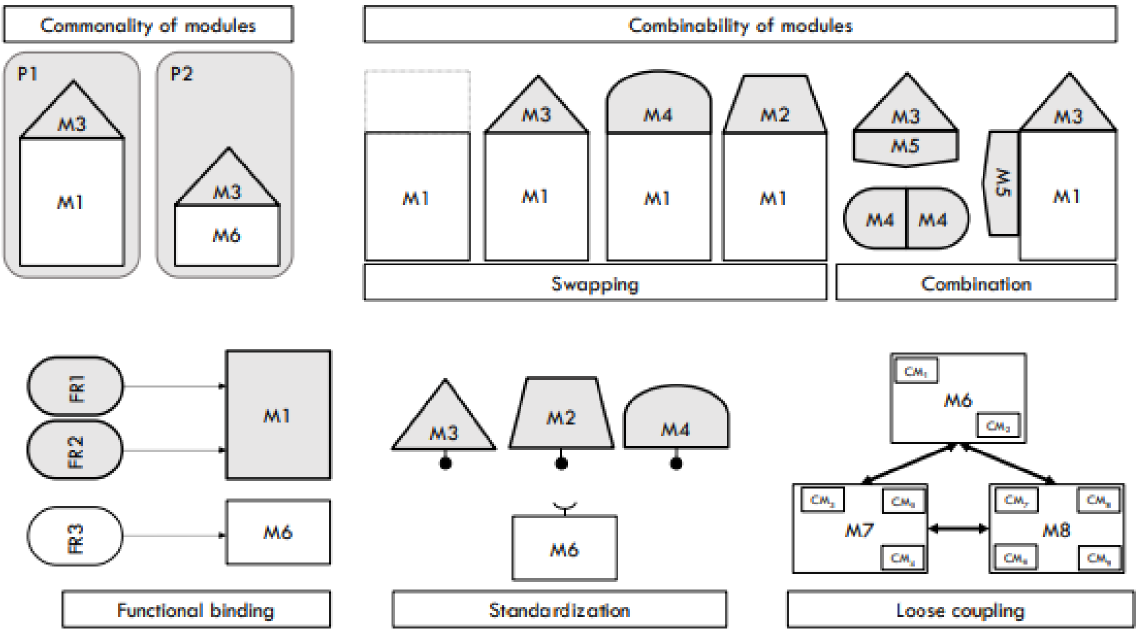

Figure 7 – Five Definitional Perspectives on Product Modularity, copied from Mertens (2020, p. 38)

Creating a modular product architecture out of an existing product architecture is realized through the process of product modularization. Mertens et al. (2022) describe this process as a three-step procedure, which encompasses the decomposition of the current product architecture, its analysis, and the rearrangement of a product's components. Hence, product modularization embarks the design and the identification of modules and may be understood as "defining modules into the product architecture" (Bonvoisin et al., 2016, p. 490).

We adopt the definition of modular design from Wouters and Stadtherr (2017, p. 62), which reads as follows.

> *"An architectural and strategic design philosophy that enables a firm to separate and recombine components within a product family or among products. Technical implementation is realized through functional independence and standardized interfaces among modules."*

2.4.4 Degrees of Modular Product Design

Having defined product architecture and its modular and integral typologies, it is important to distinguish among the different degrees of modularization that a company can employ. The decision to use common components can be made on an operational level and implemented within a short term. Employing modularity in a broader sense – by developing joint platforms from which individual product variants are derived – constitutes a strategic decision requiring top management commitment (Gebhardt et al., 2016). Thereby, we distinguish three distinct degrees of modular product design, the use of common components, the use of shared modules, and the joint use of product platforms.

Component commonality

Components serve as building blocks for modules and platforms and are the smallest units of a product (Mertens et al., 2022). Commonality implies sharing components, i.e. using the same version of a component, across many product architectures (Fisher et al., 1999; Wouters et al., 2011). Labro (2004) used the latter definition for her review of the cost effects of component commonality, finding that component commonality is mainly analyzed in the operations management literature. There exists a sub-stream within the operations management literature that analyzes the so-called component commonality problem answering the questions of (i) how "many components with (ii) what specifications to select and (iii) which product to provide with which component" (Boysen and Scholl, 2009, p. 89). Within this sub-stream, Labro (2004) identifies three research streams. The earliest one focused on inventory levels, i.e. inventory costs and risk pooling. Later streams focused on other costs affected by shared components and assumed that component sharing does not affect customer quality perception. The latest stream of research links revenues and costs related to shared components and therefore implicitly asks the question of whether and to what degree a customer recognizes shared components.

Within the scientific literature, the definition of common components could be further specified. Using a component within a product family refers to a strategy of identical parts whereas installing a component over various product generations is also known as reusing parts or carrying-over parts (Krause and Gebhardt, 2018). Component reuse can be thought of as either reactive carry-over of components from previous generations or active preplanning of product attributes to be carried over into the next generation (Zwerink et al., 2007).

We base our definition on Krause and Gebhardt (2018, pp. 129–134) and understand common components as follows.

"Common components describe already developed individual parts that are used in a new product without adjusting or modifying them. Common components can be reused from previous product generations following a carry-over strategy or installed among distinct product variants following a strategy of identical parts."

Shared Modules

Modules are the designated result of a successfully completed process of modularization (Mertens et al., 2022). They are a multitude of individual parts that jointly form a module which can be taken over from one product to another. Hence, a product family mindset is the basis for modularization. Besides, in an ongoing process, module variants are strategically defined to realize benefits from modular product design such as economies of scale and scope. In contrast to simply sharing some components, creating designated modules implies a larger investment into a modularized product architecture with an active strategic decision for multiple products to share components and modules among each other (Krause and Gebhardt, 2018).

We adapt the definition of Jiao and Tseng (2000, p. 469) for our purposes. Hence, we understand modules as follows.

"A module is a physical or conceptual group of components designed to uniquely fulfill an underlying core functionality of the fully built up product while allowing to be employed within a multitude of similar products."

Product Platforms

Product platforms are the basis for the development of derivative products of a given product family (Simpson, 2004). Jiao et al. (2007) identify two streams of research covering product platforms. The first one understands platforms in a physical manner as a "collection of "elements" shared by several products" (Jiao et al., 2007, p. 7) and strives to identify technically well-understood and timely stable elements to be shared within a product family. The second stream, exemplified by the definition of Meyer and Lehnerd (1997), aims to identify ways to efficiently exploit a platform's logic and architecture. Accordingly, a product platform is defined as "a set of subsystems and interfaces that form a common structure from which a stream of derivative products can be efficiently developed and produced" (Meyer and Lehnerd, 1997, p. 39). Another well-known definition by Robertson and Ulrich (1998, p. 20) describes a platform "as the collection of assets that are shared by a set of products", dividing these assets into four categories, namely components, processes, knowledge, and people and relationships.

A platform can be understood as the largest, standardized module of a product family, which is implemented within its derivative products (Gebhardt et al., 2016). However, a platform is independent of the lifecycle of the products that are based on it. A product platform is a special case and extension of modular product design, requiring modularly designed products with clearly defined and standardized interfaces as a prerequisite (Schuh and Riesener, 2017). Product platforms form the core of the development activities of product families. However, the classical understanding of product platforms is rather static, i.e. with a focus on predefined requirements, and lacks the agility to quickly adapt to the changed needs in today's world of dynamic markets. Scholars have therefore developed dynamic platform concepts that can incorporate updates and upgrades upon changed requirements due to external uncertainties (Han et al., 2020). There are different types of platforms like modular product platforms (Meyer and Lehnerd, 1997), scalable product platforms (Simpson et al., 2001), generational product platforms (Martin and Ishii, 2002), uncertainty-oriented product platforms (Han et al., 2020), and company-internal or external product platforms (Gawer and Cusumano, 2014). A modular platform facilitates the generation of product variants by employing existing modules (Otto et al., 2016). A scalable platform aids in differentiating variants that serve similar functions at different performance levels. A generational platform accelerates development cycles of new product generations (Jiao et al., 2007). An uncertainty-oriented platform builds on scalable and modular platforms and is designed to respond to uncertainty-driven changes in requirements (Han et al., 2020). External product platforms serve as technological foundations upon which other companies build complementary products and services, which introduces additional strategic considerations like ecosystem governance, complementor incentives, and network effects (Gawer and Cusumano, 2014).

Ultimately, the development of a product family and its derivative products aims at leveraging the platform across diverse markets and segments to realize high revenues at minimized costs (Simpson, 2004). Meyer (1997) explains different product platform strategies around the market segmentation grid. Companies can leverage their platforms horizontally (serving different market segments at the same price-performance ratio), vertically (serving the same segment at different price-performance ratios through either upward enrichment or downward limitation of the platform), or through a beachhead strategy that combines both approaches (Meyer, 1997). A product platform can be used in either modularly or integrally structured products. In fact, a platform constitutes "at the same time a form of modularisation and of standardisation" (Muffatto and Roveda, 2002, p. 14). As the largest module, the platform defines the commonality within a product family. The individual product variants differentiate from each other through the mix-and-matching of different module instances that work together via standardized interfaces (Jiao et al., 2007).

Product platforms are designed to minimize the overall costs of a whole product family and its related derivative products (Davila and Wouters, 2007). As a strategic cost management method, platform employment aims to increase a company's overall profitability. Planning a product platform therefore requires considering the cost effects of today's platform decisions on the future cost of derived products (Davila and Wouters, 2004).

We adopt the following definition of Meyer and Lehnerd (1997, p. 39) which reads as follows.

"A product platform is a set of subsystems and interfaces that form a common structure from which a stream of derivative products can be efficiently developed and produced

2.5 Results

2.5.1 Tradeoff Models and New Product Development (NPD) Questions

Tradeoffs during NPD can be illustrated in tradeoff models and typically occur as consequence of frequently asked questions during the NPD process. This subsection first summarizes frequently used tradeoff models during NPD. Second, it presents a review on frequently raised NPD questions, that lead to tradeoff situations. Taken together, the existing models as well as the frequently raised questions serve as essential baseline for our conceptual framework presented in section 2.5.2, highlighting the impact of product architecture decisions in the form of modular product design thereon.

Figure 8 presents the four-node tradeoff framework of Smith and Reinertsen (1995).

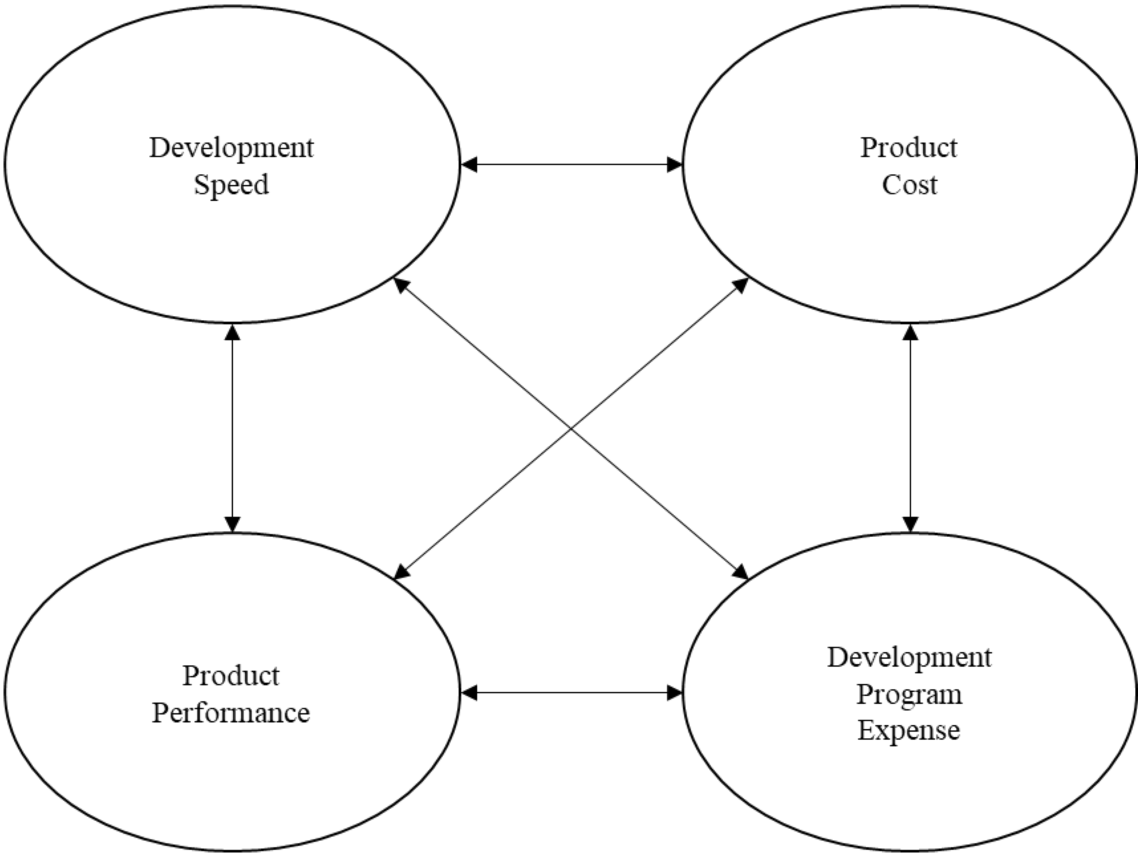

Figure 8 – Tradeoff Model, copied from Smith and Reinertsen (1995, p. 23)

The authors argue that pure optimization of one category is rarely ideal, as everything comes at a cost that needs to be evaluated (Smith, 2004). To make proficient decisions, Smith and Reinertsen (1995) suggest quantifying the effort of optimizing a certain key objective (development speed, product cost, product performance, and development program expense) and comparing these costs against their potential value for the company. As a level of analysis, the authors recommend adopting a product lifecycle perspective: optimizing one node of the tradeoff framework must yield a positive value-to-cost balance over the product's lifetime (Smith and Reinertsen, 1995). A modularly designed architecture increases flexibility in the process and reduces decision-making risk. However, Smith and Reinertsen (1995) stress that many companies rush through architecture decision-making by starting detailed design activities prematurely and only later recognize the need for tradeoffs once they discover that their initially desired target profile is internally inconsistent. Companies could reduce the need for tradeoffs by considering the architecture decision more thoroughly at the fuzzy front end (Smith and Reinertsen, 1995). Structurally, Smith and Reinertsen (1995, p. 23) distinguish time related nodes ("development speed"), cost related nodes ("product cost" and "development program expense"), and quality related nodes ("product performance"), which lays a pure development focus without considering a later commercialization of the developed products.

Within the operations management literature, the component commonality problem is a frequently studied issue (Boysen and Scholl, 2009). Labro (2004) reviews component commonality within the operations management literature and identifies three distinct evolutions of study perspectives on component commonality. The chronologically latest stream considers revenue effects of common parts and therefore considers the sales impacts that product development decisions have. One of the first studies belonging to this latest stream is the optimization-based research of Jans et al. (2008) whose tradeoff model is denoted in Figure 9.

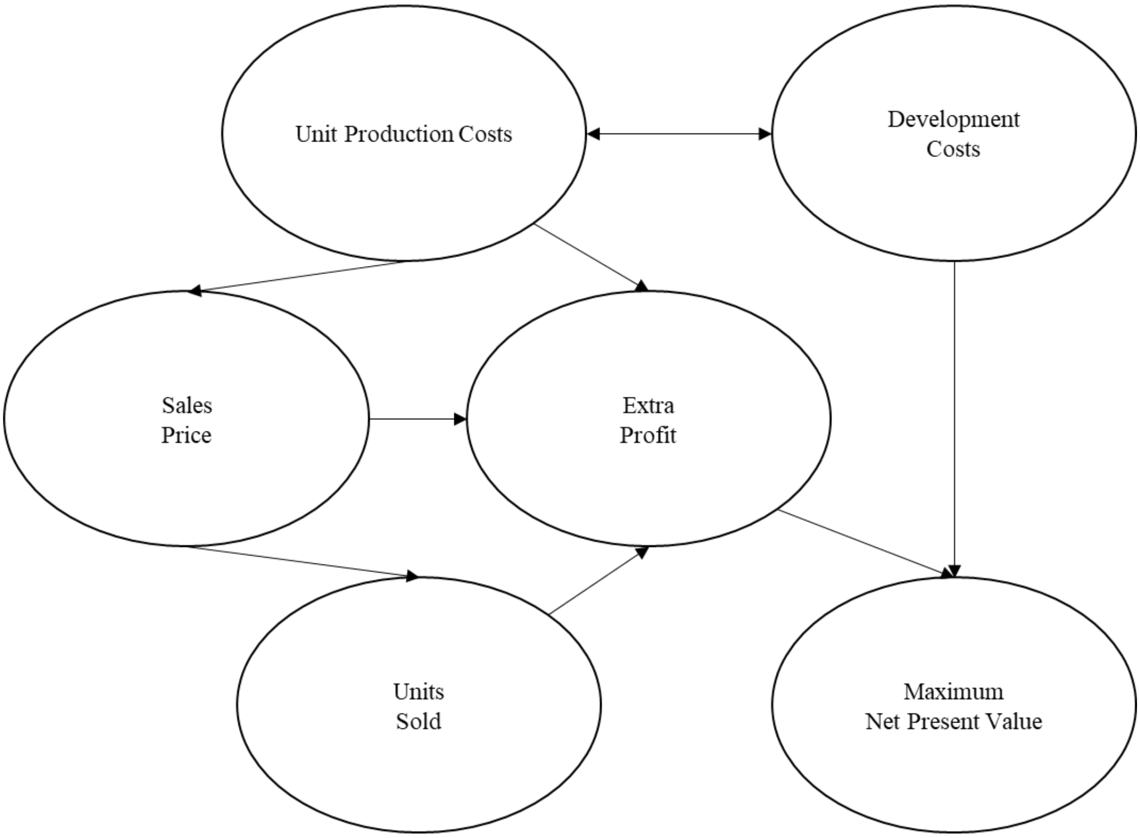

Figure 9 – Tradeoff Model, copied from Jans et al. (2008, p. 802)

The authors optimize component commonality decisions to maximize the net present value of the product subject to unit and overhead costs, achievable sales price, and total sold units. Along these key elements, several tradeoffs need to be solved to maximize the realizable net present value. Their tradeoff framework ultimately optimizes the development project's net present value subject to its costs and revenue attributes, considering a total of seven tradeoffs. The model contains no time or quality nodes, cost nodes ("unit production costs", and "development costs"), revenue nodes ("sales price" and "units sold") and analyzes tradeoffs from a profit-driven total net present value perspective (Jans et al., 2008, p. 802). Hence, the focus of this framework is rather on the product commercialization via a maximized net present value than on the typical development goals of time, cost, quality.

Wouters et al. (2016) provide a tradeoff framework that distinguishes between NPD tradeoffs at the product level and those affecting the project level as presented in Figure 10.

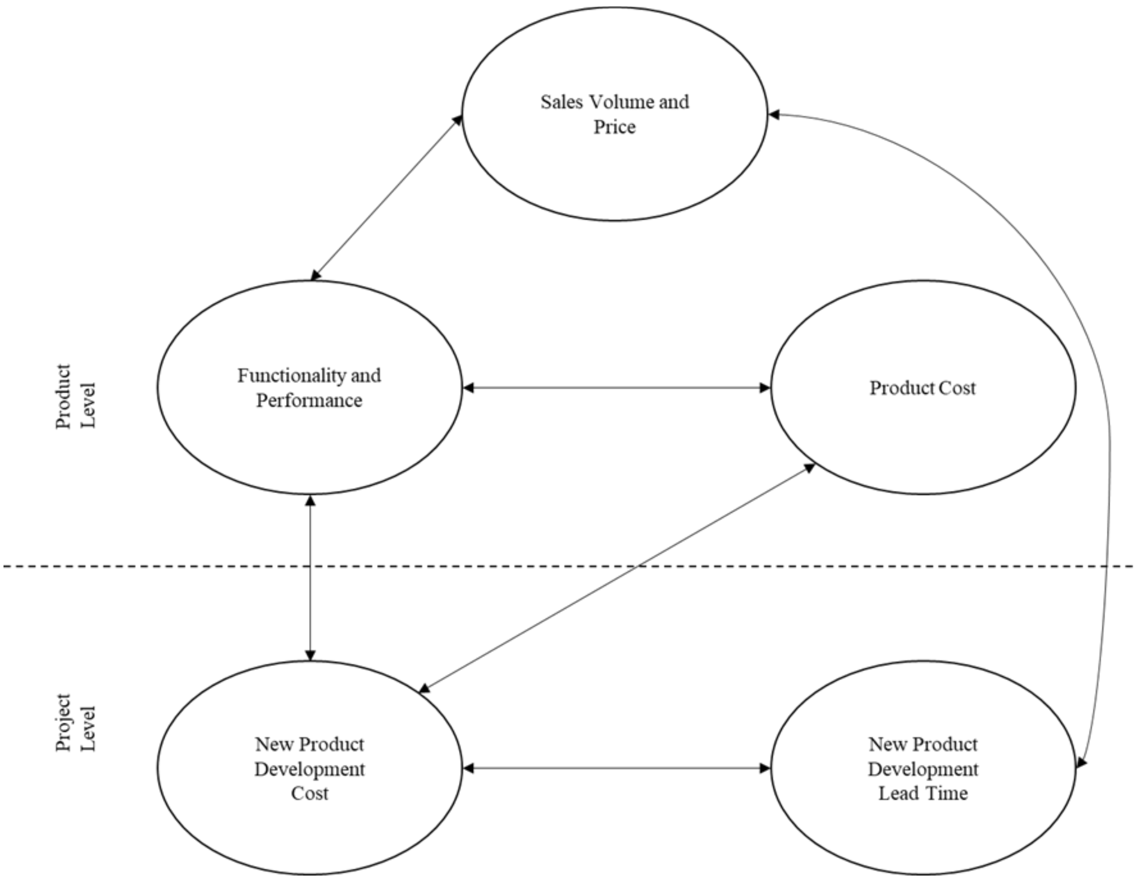

Figure 10 – Tradeoff Model, copied from Wouters et al. (2016, p. 148)

Product-level tradeoffs concern the product's direct costs, its aspired functionality and performance, and the market-related aspects of sales volume and price. Project-level tradeoffs account for overhead costs – which by definition cannot be allocated to a single product in a causal manner – and the research and development (R&D) related lead time. The framework suggests that individual tradeoffs between two initially divergent performance indicators, such as product costs and product properties, can be resolved by adjusting one or both targets. The model incorporates time nodes ("new product development lead time"), quality nodes ("functionality and performance"), cost nodes ("product cost" and "new product development cost") and revenue nodes ("sales volume and price") (Wouters et al., 2016, p. 148). Hence, the model considers product development as well as the commercialization of the developed product fully.

Thore Olsson et al. (2018) provide a tradeoff model directly inspired by industry insights as shown in Figure 11.

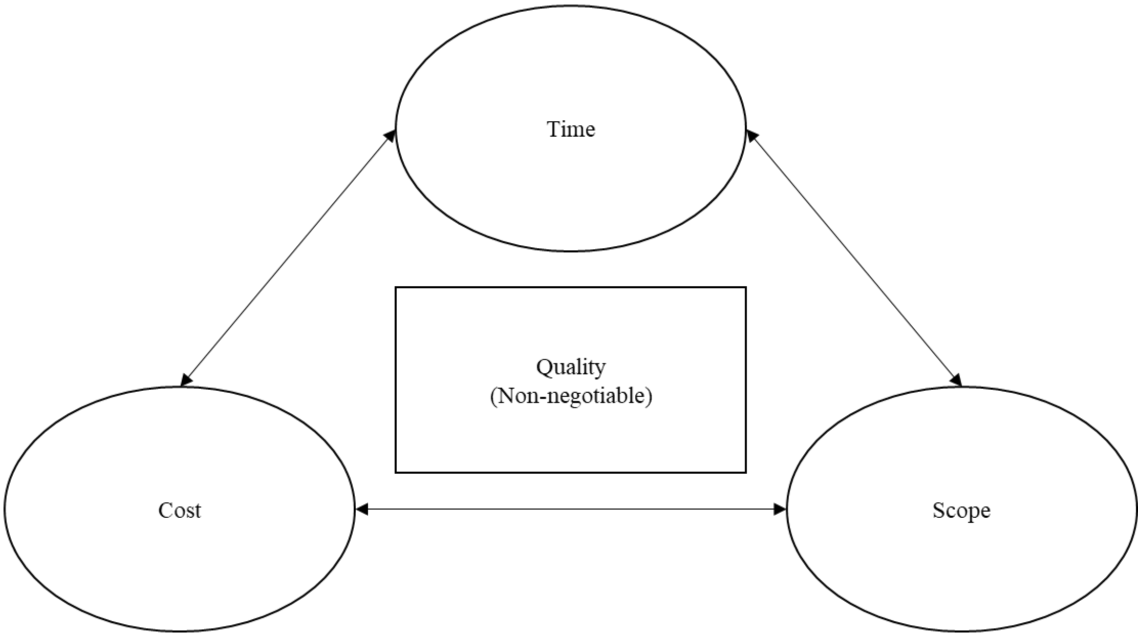

Figure 11 – Tradeoff Model, copied from Thore Olsson et al. (2018, p. 1070)

The authors explain how project key performance indicators of time, cost, scope, and quality influence decision-making during NPD. In their setting, they assume that a product's target quality must not be compromised. The performance indicators of cost, time, and scope must therefore be aligned to fulfill the quality targets. Given cost deviations at a sub-assembly level, tradeoffs typically arise once neither a cost target shift (resulting in tougher targets for other subassemblies) nor intensified cost work (e.g. supplier renegotiations) resolves the gap. In such situations, decisions on scope, time, and cost must be made to satisfy quality requirements (Thore Olsson et al., 2018). The quality node in this model is explicitly fixed, illustrating that the individual nodes can follow an explicit preference order.

Besides these NPD-specific tradeoff frameworks, the general iron triangle of project management with a cost, time, and quality node describes the tensions of any project, which therefore also applies to NPD projects. Basically, the just explained framework of Thore Olsson et al. (2018) is a case-specific adaption of the general iron triangle of project management. Pollack et al. (2018) reviewed the literature on the goals denoted in the iron triangle and noticed that the quality node is also partially replaced or measured by performance, scope, or project-specific requirements. We depict the iron triangle of project management alongside further tradeoff models – the pentagon model of Rose (2013) and the cost sensitive model of Bakker et al. (2020) – in the appendix.

Based on these models, we derive the need to incorporate distinct nodes related to quality, costs, time, and the post-NPD revenue-driven commercialization. Besides, to provide a full picture by our conceptual framework, we consider a multi perspective view distinguishing among single product effects and entire project effects. The broader project perspective allows for detailed discussions that product architecture decisions in the form of modular product design play in handling the identified tradeoffs. Hence, we structure our conceptual framework to consider a product as well as a project view on the target dimensions of time, quality in the form of functionality and performance, and costs. These individual targets are steered by an overall profit maximization goal.

Besides having a structural level of analysis in the form of a tradeoff model, we are concerned about what situations in the development process lead to conflicting decisions that yield tradeoff situations. Having a clear picture at which occasions tradeoffs could occur, allows us to map and identify the tradeoff impacts of product architecture. In the literature, we found three influential literature reviews – Krishnan and Ulrich (2001), Jiao et al. (2007), and Harland and Yörür (2015) – that have collected central NPD questions which we expect to lead to tradeoff situations.

Krishnan and Ulrich (2001) identify product development decisions within a project such as which components will be shared across which product variants or which assembly process should be used. Jiao et al. (2007) review the product platform development process and provide a holistic view of product family design and development. While the authors do not directly collect and enumerate typical questions, their holistic view clusters fundamental issues during family development that trigger tradeoff situations, starting with the identification of customer needs and ending with operational logistics variables (Jiao et al., 2007). Harland and Yörür (2015) identify 21 decisions made during product platform development projects (PPDP). They group these decisions into the categories of market-related and synergy-related decisions, whereof the former category is deemed to increase a company's competitive advantage and the latter one is oriented on potential cost reduction opportunities for the applying company (Harland and Yörür, 2015). Within the first category exemplary decisions are made upon e.g. variant specification whereas the latter category encompasses, among others, decisions upon the manufacturing strategy. Accordingly, we structure our model to consider distinct facets that need to be considered that we group as variety management, manufacturing flexibility, and design options.

2.5.2 Conceptual Framework

Figure 12 presents our conceptual framework. It contains three models: A financial tradeoff model, an impact model of modular product design, and an impact strength model.

The financial tradeoff model illustrates the tradeoffs decision-makers need to handle during NPD. The five tradeoffs – indicated by the small letters a–e – are each discussed in a dedicated subsection. The plus/minus signs on the top right-hand side of the target nodes – functionality / performance, new product development lead time, direct and indirect costs – denotes whether the individual node should be maximized or minimized from a profit maximization perspective. Like Wouters et al. (2016), we distinguish a product and project level of targets to be considered in maximizing the individual tradeoffs that is affected by an incentivization dilemma resulting from limitations in management accounting (Israelsen and Jørgensen, 2011; Nørgaard et al., 2025; Thyssen et al., 2006).

The impact model illustrates how the five definitional perspectives of modular design from Salvador (2007), that were also discussed earlier in section 2.4.3, enlarge the decision-options in handling the financial tradeoffs as they yield modularity impacts. These impacts – which we summarize as variety management, manufacturing flexibility, and design options – influence the decision-making at the individual tradeoff arrows. They are oriented at the previously referred NPD questions (Harland and Yörür, 2015; Jiao et al., 2007; Krishnan and Ulrich, 2001).

The degree by how much the modularity impacts manifests is driven by the degree of modular product design, that we defined as three distinct steps of common components, shared modules, and product platforms that become economically realizable once a certain minimum product volume is reached (Krause and Gebhardt, 2018; Lau et al., 2007). Therefore, the impact strength model illustrates the modularity options that decision-makers could use to manage financial tradeoffs.

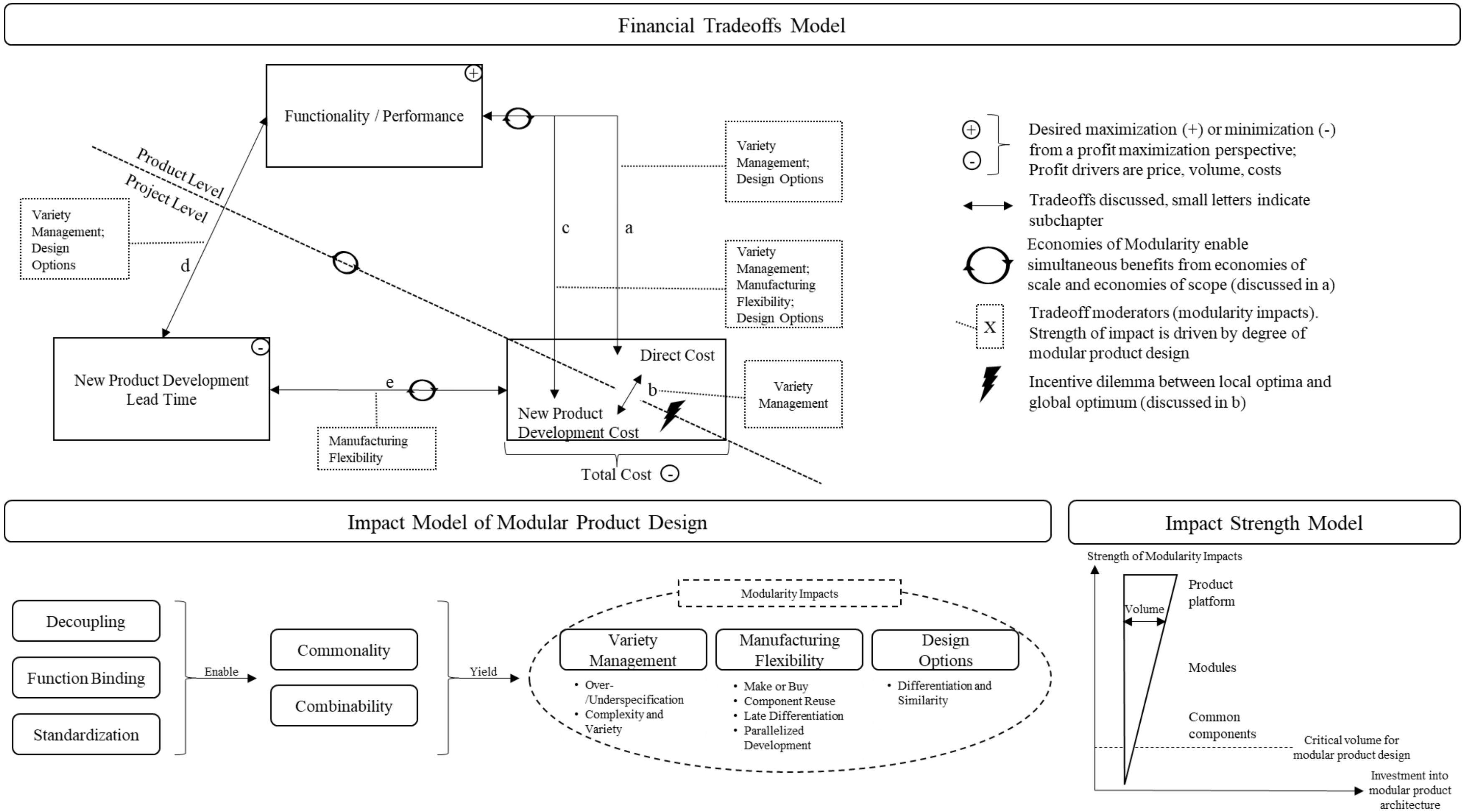

Figure 12 – Conceptual Framework on Financial Tradeoffs during New Product Development (NPD)

2.5.2.1 Tradeoff (a) – Direct Cost and Functionality and Performance

The core areas of product-level decision-making concern the product's functionality and performance, and direct cost base. Thereby, functionality and performance contribute positively to profits as they increase the appeal of the product boosting sales volume or allowing to charge a higher retail price, and costs contribute negatively. The tradeoff is characterized by the positive relation between product functionality and direct costs combined with opposed targets assuming an overall target of profit maximization. (Wouters et al., 2016).

We observe the impacts of modular design through variety management – over-/underspecification, and complexity and variety – and design options allowing to combine product differentiation at the outside while having highly similar products at the (technological) inside.

Modularity Impact – Variety Management

Modularly structured products are designed to share modules and components across product families and across products that may even target different market segments. A shared module or component may therefore not meet exactly the requirements of every underlying product. Hölttä et al. (2005, p. 1) state that "there is generally a price to be paid for modularity in terms of other product characteristics" as products could be otherwise developed in a dedicated and optimized way.

The price to be paid for a reduced development effort manifests as over- or underspecification. On the quality side, a decision about over- or underfulfilling product requirements must be made. On the cost side, the degree of mismatch translates into development and unit costs. Overspecification refers to defining a product or component "beyond the actual needs of the customer or the market" (Ronen and Pass, 2008, p. 162). Therefore, Marzi (2022) classifies it as an example for a beyond the needs specification of overfeaturing a product during the development process. Concerning the direct costs of shared components, Thyssen et al. (2006, p. 253) illustrate that only "in the rarest of cases, however, will the variable cost per unit of the common module be less than the variable cost per unit of each of the otherwise product-specific modules that it substitutes". Further, they argue that it is indeed likely to incorporate higher variable costs for the shared module than the most expensive part it replaces would demand. Accordingly, cost degression effects like discounts due to economies of scale, lower set-up costs due to economies of scope, and learning curves need to outweigh the costs incurred due to over specification in order to realize a positive business case (Thyssen et al., 2006). Desai et al. (2001) employ a numerical example that vividly illustrates how over/underspecification creates tension between the direct cost and revenue goals of the product-level tradeoff. They present two products – one intended for the upper market segment (Product H) and one for the lower segment (Product L) – which can be designed uniquely (Unique Configuration) or share a common module specified to fulfill either the upper market requirements (Premium Configuration) or the lower market requirements (Basic Configuration). In the Premium Configuration, where both products use the upper-specified common part, the achievable market price of Product H decreases while that of Product L increases. Premium customers of H are unwilling to pay the same price, since the shared component with lower-segment Product L dilutes the premium position, even though H's attributes remain unchanged. Customers of L, however, appreciate the increased product quality and are willing to pay more. In the Basic Configuration, only the price of H decreases, while that of L stays constant. Although

Product H does not offer lower attributes in the shared premium configuration than in the unique trim, it possesses a weaker position to justify its premium price (Desai et al., 2001).

This effect between the (perceived) quality and revenue dimension is described by the notion of commonality (Kim and Chhajed, 2000). As Heikkilä et al. (2002, p. 24) put it, “an Audi owner knowing that a considerable part of the components in his car are the same as those used by Skoda might not be totally happy with the situation”. Revenue effects must not be neglected in the sharing decision (Boas, 2008), though they occur only if the customer is aware of and concerned about shared parts (Wouters and Stadtherr, 2017). Most scholars postulate the general rule to share invisible parts that do not deliver added customer value, while investing R&D budget in product-differentiating unique solutions (Heese and Swaminathan, 2006). Components can generally be distinguished by whether they possess a strong or weak influence on the overall product quality . Referring to the product level tradeoff, parts with weak quality influence – such as braking systems (Fisher et al., 1999; Ramdas, 2003) – should be assessed on a pure cost base omitting any revenue effects (Boas, 2008). Such components need only deliver a minimum performance level as customers “do not care about these components” (Fisher et al., 1999, p. 300) given they fulfill a certain performance threshold.

While individualization may be desired and rewarded by the market, it induces variety and hence complexity to the company. Whereas variety describes the market offering a company supplies to meet demands, complexity is the effect resulting from variety on internal operations. The degree to which complexity characterizes a corporate issue depends on the company’s general ability to manage it (Roy et al., 2011). Hence, complexity is not necessarily negative as scholars distinguish necessary complexity (needed to increase the value proposition) from unnecessary complexity (which should be eliminated) (Anderson et al., 2006).

Generally, complexity costs are hard to quantify and often underestimated. Although they occur partly on a direct cost basis, many effects are realized as overhead, making it difficult to allocate an exact amount to the cost driver of complexity. Scholars differentiate direct efforts (higher direct costs, investments, one-time costs) from indirect effects (rework, storage costs, quality costs), the latter being particularly challenging to assess in practice (Herrmann and Peine, 2007; Tanner et al., 2003). They typically appear as delayed jump-fixed costs as decisions to increase the variety are made at the start of NPD while cost effects materialize at later stages (e.g. during production). A slightly increased level of complexity may be absorbed by existing processes, but the overall cost level rises sharply once a threshold is reached that existing processes cannot accommodate (Gebhardt et al., 2016).

Complexity is central to the product-level tradeoff since the general belief holds that either costs or revenues are optimized at the expense of the other. Modular product design, common parts, and product platforms provide an instrument that combines both goals of revenue maximization and cost reduction. Modularity possesses the potential to relieve this binary conflict by allowing companies to increase external variety (the product offering sold to the market) while lowering internal variety (the number of distinct components) (Roy et al., 2011; Windheim et al., 2018). A company operating in a competitive environment will increase its external variety as long as the marginal revenue increase exceeds the resulting marginal cost increase (Herrmann and Peine, 2007, p. 654). Lancaster (1990) identifies three factors influencing optimal variety: economies of scale, the perceived added value of variety for the customer, and market structure, i.e. “variety is greater under monopolistic competition than under monopoly.” The question of what variants to offer (Krishnan and Ulrich, 2001) is thus typically answered by weighing potential cost and revenue effects against each other.

Modular design – by enabling individualized products at the cost level of standardized products – allows to combine both benefits. Commonly employed parts designed for different variants of a single product (increasing scale) while used across multiple derivatives (increasing scope) serve as an example realizable through standardized interfaces (Schuh et al., 2011). The economies of modularity describe the cost reduction mechanisms that companies exploit through modular product design across the product lifecycle. They represent the joint effects of economies of scale and scope in a narrow sense (Reichwald et al., 2006). Broader definitions add economies of learning to this construct (Skirde et al., 2016).

Economies of learning describe increased efficiency through repetition of standardized work yielding faster task completion (without any deficiencies in quality). Hence, these efficiencies reduce the allocated overhead costs for any produced part by decreasing their production costs. Therefore, economies of learning refer to the possible gain in efficiency related to a company’s internal complexity. A related concept to economies of learning are the economies of experience, which collect all impacts realized through higher volumes. Whereas economies of learning are based on cost savings that are realized through higher volumes due to increased efficiencies, economies of experience are based on the relative development of the market price compared to the sold quantities. Hence, economies of learning are derived from internal effects within the company, economies of experience are derived from external market related effects (Steven, 2005). As such, the economies of experience are directly linked to a company’s external complexity, while the economies of learning reflect the capability of a company to deal with its internal complexity. As long as internal and external complexity costs (and the economies from learning and experience) are directly linked, companies do not capitalize on increased variety. However, modular product design allows to break the direct relationship between external and internal complexity to generate a relative gain in economies of learning. Accordingly, the quotient of the increase in economies of learning to the increase in economies of experience describes the cost saving potential of modular product design compared to an integral product design (Skirde, 2015).

Economies of scale are the most frequently cited positive effect of modular design. Modularity enables the sharing of internally invisible parts through standardized interfaces, increasing the quantity of identical components while reducing the overall number of different parts (Windheim et al., 2018; Wouters and Stadtherr, 2017). Concerning the product level tradeoff, scale benefits materialize in development and manufacturing, while potential disadvantages in terms of a lowered price position occur at the sales side (Pasche and Sköld, 2012). Cost benefits come from increased lot sizes, higher sourcing quantities for external parts, reduced development time, and shortened time-to-market (Fixson, 2006). Employing already-developed parts or parallelizing development processes provides modularity-based means to reduce time-to-market. Timing is a factor in a company’s ability to realize its target price, since demands vary over time and first-mover advantages may occur. Inabilities to meet peak demands result in lost sales that may need compensation through price discounts to avoid unused production capacities (Prasad, 1997). Scale economies are usually pursued by companies following cost leadership strategies, scope economies by those following product differentiation strategies, which are traditionally opposing strategies.

Some scholars warn that research on the economies of modularity tends to exhibit overestimation errors (Boas et al., 2013). Generally, the discussions on modularity tend to be positively biased (Pasche and Sköld, 2012), prompting more critical studies like Fixson and Park (2008) or Magnusson and Pasche (2014) highlighting negative effects of modularity in the cost-revenue tradeoff.

Modularity Impact – Design Options

An increased use of common parts may lead to products that are too similar, lacking distinctiveness from each other. A too-high degree of similarity will provoke product cannibalization. Typically, scholars discuss this effect in situations where different products satisfy a customer's need in different ways – for instance, a plane and a car both serve as means to travel between two destinations. In terms of offering two similarly perceived products, one intended for the premium segment and one for the economy segment, cannibalization may result in a shift of premium customers to the economy segment, of economy customers to the premium segment, or a mix of both (Kim and Chhajed, 2000).

The degree of cannibalization is again influenced by the tradeoff between (perceived) quality and revenue. The threat depends on the individual preference structure in the customer groups as it is more pronounced when one segment dominates the other. That means, there are at least two groups of consumers with vertical consumer heterogeneity, where one group puts more emphasis on all product properties than the other. In many markets, however, different customer segments value contradicting product qualities. A potential premium car customer may derive high utility from product design, whereas a more price-sensitive customer may be mostly interested in practicability. Such diverging preference structures may alleviate the threat of cannibalization despite the use of common parts between products (Kim et al., 2013).

The use of product platforms is a central enabler for employing standardized common components while creating distinct individualized products through mix-and-matching. Effective use of product platforms balances the cost-revenue tradeoff by capitalizing on economies of differentiation while saving through economies of commonality. A central point is made by Robertson and Ulrich (1998, p. 21) as they state that "customers care about distinctiveness, costs are driven by commonality". Hence, the revenue side of the product level tradeoff is steered via distinctiveness whilst the cost side of the product level tradeoff is optimized via component commonality. A promising design philosophy enabled through product platforms is mass customization. Modularly built products are a precondition for mass customization, making product modularity a strategic choice for benefiting from the advantages of modular portfolios (Ro et al., 2007). The underlying idea is to generate economies of scope and scale by delaying the differentiation of final products and capitalizing on common parts across different product variants within a given product family. Individual customer needs should be satisfied while keeping a mass-product cost structure (ElMaraghy et al., 2013). Mass customization increases product differentiation, which may constitute added value for the customer.

In general, the value of a consumer good can be understood as a gained increment of utility compared to the second-best option (Piller, 2004). Especially for equally valued goods, a customer buys the product offering the highest difference between utility and price (Dolgui and Proth, 2010; Kim and Chhajed, 2000). Higher value may translate into a higher willingness to pay (WTP) that justifies a higher market price. Holding costs constant, a mass-customized product realizes a higher product margin, holding the margin constant, it could afford higher direct costs. Empirically, studies have found WTP increases of up to 150% for the gained utility of customized products (Piller, 2004), though this depends on the product and market. Bardakci and Whitelock (2004) studied readiness for mass-customized cars in the UK, defining a customer as ready if willing to pay a price premium, wait for delivery, and spend time designing the product. Their hypothesis of willingness to pay a premium was only partially supported, leading them to recommend a dual strategy of customization and standardization as best approach to handle the product level tradeoff (Bardakci and Whitelock, 2004).

2.5.2.2 Tradeoff (b) – New Product Development (NPD) Cost and Direct Cost

The overhead-versus-direct-cost tradeoff reveals a fundamental tension between local product-level optima and global portfolio-level optima that constitutes a distinct architecture impact. Existing accounting techniques generally maintain a single-product rather than a portfolio focus, which is why the ideal balance between development and direct costs is often not realized. In other words, sharing modules "probably best illustrates the need for a broad view of cost management" (Davila and Wouters, 2004, p. 22) – a task for management accountants and their toolset. Despite this need, few research contributions address how to steer and account for modularity and local inefficiencies (Wouters and Stadtherr, 2017). Classic instruments and accounting systems do not consider total profit at a portfolio level but focus on single-product profitability (Davila and Wouters, 2004). The problem herein lies in the fact that individual project managers are not willing to accept higher direct costs than necessary on the individual product level as they are not incentivized to do so for the sake of reduced development efforts, higher volumes, and higher corporate profitability (Ro et al., 2007).

One of the rare examples of how classic accounting systems prevent sharing decisions is given by Israelsen and Jørgensen (2011). The authors introduce the underlying problem by making use of a simple example, where a company offers three products that could technically use a common module. In the first scenario, the case company develops a module that is shared among products A and B, and a dedicated standalone part for product C. Herein, the net profit of products A and B is 300 and the net profit of product C equals 40, which results in an overall portfolio profitability of 340 for the company. In the second scenario, the company develops a higher-specified module, which fulfills the requirements of all products. This more advanced module gets installed in all three products resulting in a net portfolio profit of 400 for the company. The question that the authors raise is how to motivate the individual project managers to agree upon the development of the higher specified module which could be shared across the entire portfolio. In the sense of the Pareto principle, no project manager should be worse off through modularization than without. Consequently, the project managers of projects A and B expect a minimum allocated profit of 300 and project manager C a minimum profit of 40. At the same time, no more marginal profit increase can be attributed to the added project than is generated by its inclusion to the portfolio. In the given example, the maximum increase in project C's profitability equals 60 which is the difference in the overall portfolio profits generated in the two scenarios. In addition to this simple example, the authors also take up a more realistic scenario in which the net profit of the single project P6 deteriorates on its own, but the portfolio profitability improves by sharing a module across the entire product range. In order to create an incentive for P6's project manager, the authors propose to start on the individual project level by calculating the project specific contribution margin given the variable costs of the collectively employed modular part. Hereof, the authors subtract the net profit which the project would be able to achieve using project-specific components instead of the common module (in the simple example this was 40 in the case of project C) and the marginal portfolio profit increase realized by adding the analyzed project to the class of module users (in the simple example this was 60 for project C). The authors stress that the latter listed marginal profit improvement is often an unknown figure at the project level, which is why they mention the possibility to alternatively split the overall gained marginal profit increase evenly across the projects or across the units subject to not counteract the company specific incentive system. The deduction of these two items from the contribution margin leads to the project specific allocation of development costs needed to develop the commonly used module. In the case project P6, which would individually be less well off, this allocatable sum would be a negative number. To incentivize participation, the authors introduce a lump sum credit that outweighs P6's otherwise incurred losses, funded by the other projects that increase their profit through modularity (Israelsen and Jørgensen, 2011). Besides, Nørgaard et al. (2025) provide another simple example of a bike manufacturer that sells three bikes that could either share a frame which would be overspecified for two of the three bike models or develop three individual frames. In their example, the partly overspecified solution needs and higher direct costs to be weighted against the savings of shared development effort and reduced overhead costs. They use this argument as baseline to motivate for management accounting analysis based on distinct level, the product, subsystem, and component level, to justify architecture decisions.

These examples illustrate how unfavorable decisions are likely made due to a lacking holistic perspective and total cost incentivization. Kee and Matherly (2013) stress the importance of coordinating decisions whenever product interdependencies are present and advocate for implementing target costing at the portfolio level. While theoretically possible to use lump sums or the weighting of single product targets by compensating their override at a portfolio level, a centralized decision-making approach is key to operationalization (Ortelbach, 2005).

Modular product architectures thus enable the realization of global optima concerning the ideal tradeoff between direct material and indirect development costs – but only with portfolio-wide incentivization and coordinated decision-making across the entire portfolio. While this provides a theoretical advantage, information transparency is limited in practice, which is why the ideal share of development activities compared to direct cost expenses is hardly identifiable. The lack of portfolio focus in management accounting tools and incentivization impedes the structured realization of this ideal share in reality (Grønvald et al., 2026). In practice, decisions on the architecture often face no dedicated analysis of direct and development costs and may instead be based on gut feeling (Jørgensen and Messner, 2010, 2009).

2.5.2.3 Tradeoff (c) – New Product Development (NPD) Cost and Functionality and Performance

This tradeoff depends critically on the level of analysis. From a pure product perspective, development resources should be allocated to value-adding functionalities for the customer. Why should a product invest more into additional functionalities than those the customer desires (Davila and Wouters, 2004)? This question is especially pertinent given the positive relationship between the number of functionalities – i.e. product complexity – and development costs.

Modularity Impact – Variety Management

A more complex product requires more man-hours and potentially more departments and specialists (Agndal and Nilsson, 2007). Applying an activity-based costing logic supports this, since more activities increase the overhead cost base (Desai et al., 2001). Over-specified components – as discussed in section 2.5.2.1 – thus incur not only higher direct costs but also higher development costs. Labro (2004) provides a comprehensive review of these dynamics through a management-accounting lens and cautions that the often-repeated claim that commonality reduces cost is more subtle than the operations literature suggests: once costs are disaggregated by activity-based hierarchy level, common components may carry higher unit-variable costs because they must meet the envelope of the most demanding variant, partially offsetting the savings in product-sustaining and batch-level activities. However, once we shift to an overall project and portfolio perspective, additional overhead for supplementary functions can be understood as an investment in the product family's functionalities that may be amortized over the component's lifetime across all employing products (Thyssen et al., 2006). When components are designed modularly and employed across a diverse set of products, higher volumes reduce the per-product overhead allocation. This is the project-level manifestation of the economies of scale discussed in section 2.5.2.1. At the product level, scale reduces direct material costs per unit; at the project level, it reduces allocated development overhead per product.

The critical question is whether the required number of component-employing products can be secured to justify larger investments for added functionality. Park and Simpson (2005) practically illustrate this volume-sensitivity and stress that increased sharing and higher overhead costs may only be a good idea once the required number of component users is in place. Using a commonly employed module may thus allow companies to secure higher product performance levels than individually developed parts would achieve, as their development expenses can be spread more widely. However, once pure performance maximization is the goal, a commonly employed part is likely inferior to dedicated development (Mikkola, 2006). Van Os et al. (2023) contribute a framework to conduct sensitivity analysis for evaluating different product architectures against each other considering development cost and product performance. The initially higher development costs for shared modules can be allocated on a higher amount of employing final products to create a financially opportune option concerning the total cost base on a portfolio level. Consequently, product architecture impacts of overspecifying components as well as component reuse and adaptability can be favorable on a product family level once the minimum volume is realized. In such case, the architecture decision to go modular facilitates the creation of high performing products through reusing a limited number of different components.

Modularity Impact – Manufacturing Flexibility

Kamrad et al. (2013) provide an economic model analyzing the benefits of modular architecture for reacting to technological changes. The gained flexibility pays off when adapting to customer-specific needs is considerably less expensive than redeveloping an entirely new product. If a product's upgradability or adaptability of functionalities to customer requirements is a crucial success factor, a modular architecture may relieve the tradeoff between limited development budgets and required product functionalities. These benefits are however not free as the common platform typically must be over-specified relative to any single end item (Thyssen et al., 2006). Many studies analyze the tradeoff between development cost and functionality and performance in conjuncture with development lead time. For example, Lin et al. (2012) provide evidence for a moderating role of product quality and its development cost on the relation between development lead time and product success. Therefore, the modularity impacts of reusable components or late differentiation provide a lever on the profitability of an individual product.

Modularity Impact – Design Options

Reusable modules enable the configuration of distinct performance levels and whilst maintaining a highly similar product architecture. Using already developed components allows allocating development costs over multiple product generation reducing the per product allocated sum. Hence, a modular product architecture provides options to simultaneously improve the functionality and performance of a product whilst keeping its development costs at a moderate level (Thyssen et al., 2006). Thereby, it is again important to secure a minimum required volume per shared component to make initially higher development expenses an attractive decision option. Literature on the optimal product family design therefore investigates the best design choices to keep external differentiation high but limit overhead costs. The individual levels of modular design – i.e. from component sharing to platform design – offer different modularity rewards but require also different levels of overhead investments (Song et al., 2021).

2.5.2.4 Tradeoff (d) – New Product Development (NPD) Lead Time and Functionality and Performance

Market timing can be a crucial success factor and is determined by decisions made during NPD. Companies face pressure to develop innovative products quickly, especially in high-tech markets and in industries with short lifecycles (Yu et al., 2021). Managers must decide when a product should be introduced and which characteristics it should have. A short development time allows securing first-mover advantages that may prove decisive depending on the industry (Gómez-Villanueva and Ramírez-Solís, 2013). A long-lasting, well-built product, however, may serve as a basis for building a satisfied loyal customer base that repurchases and promotes the company through word of mouth (Calantone and Di Benedetto, 2000). In competitive environments, decision-makers regularly find a situation where they can only be first to market once they overshorten the NPD process – e.g. by eliminating quality assessments and tests. The tradeoff thus describes choosing between risking lost revenues (from late market entry affecting sales volume or enforceable retail price) and accepting the risks of early entry with a potentially inferior product (Calantone and Di Benedetto, 2000).

The tradeoff between functionality and performance, and NPD lead time describes the decisions corporate managers must make to find the optimum between being fast and developing a high quality product. Rather surprisingly, scholars did not study this tradeoff until Cohen et al. (1996) provided a highly cited contribution with guidelines on how managers should decide between time-to-market and product performance to maximize lifecycle profits (Ho and Kim, 2022). Their mathematical model yields five managerial guidelines: (1) invest the most development time in the most productive stage, provided improvements add value to the overall proposition; (2) being fast to market is not necessarily better, especially with intermediate rivalry and an existing predecessor product; (3) bringing premature products to market that lack exhaustive testing carries potential danger; (4) the importance of bringing highly performant products depends on the existing performance level in the market and the competitor products currently available; and (5) improved NPD processes are always beneficial, even if they do not necessarily lead to earlier market launch (Cohen et al., 1996). A recent mathematical model by Yassine and Souweid (2023) considers the influence of product complexity, product newness, and supply chain configuration on the performance-timing tradeoff. For relatively simple NPD processes, the model suggests investing time in the design phase to optimize functionality. For complex and highly innovative products, however, time should be committed to system design. The study also suggests that incorporating suppliers can contribute to an overall reduction in development time (Yassine and Souweid, 2023).

Besides, a short development time enlarges the strategic window to find the best market introduction timing. Langerak et al. (2008) jointly analyze the effects of development costs, market-entry timing proficiency, and product superiority on profitability. The authors make the important distinction between NPD lead time and market-entry timing, i.e. a short development time does not automatically imply an early market introduction. This allows separating the effects of development speed and timing proficiency on the product’s overall performance. Their empirical findings show a positive relationship between timing proficiency and product success, moderated by development lead time and sales volume (Langerak et al., 2008). Companies are therefore interested in reducing development time to enlarge their flexibility in choosing market timing. The right timing depends on multiple factors including demand dynamics, competition intensity, product quality, and the speed of innovation within the industry (Yoon and Rim, 2018). The decision is influenced by quantitative tactical aspects (e.g. expected development costs) and qualitative strategic aspects (e.g. the company’s overall mission) (Lilien and Yoon, 1990).

Modularity Impact – Manufacturing Flexibility

This tradeoff introduces a central architecture impact namely the manufacturing flexibility enabled by modular design, which allows for parallelized development activities. Since components in a modular architecture map to functions on a one-to-one basis, concurrent engineering and parallel development in separated teams – both internally and in cooperation with external suppliers – become feasible (Sanchez and Mahoney, 1996). A higher degree of modularity in the product architecture is even found to be a reinforcing factor for the outsourcing decision of companies. Anderson and Parker (2002) find an inverse relation between the degree of modularity and the cost penalty of integrating outsourced parts. The option for a high number of externally sourced parts allows parallelizing a large degree of the NPD process, possessing significant potential for lead time reduction. Standardized interfaces also enable simpler and faster updatability as new product versions can be created by exchanging central modules while reusing other components in the new version (Lau and Yam, 2005). Since processes can be conducted simultaneously, testing activities before market introduction can be shortened as well (Ulrich and Tung, 1991). An important factor in determining the ability to conduct processes in parallel is the amount of interaction required between individual components. Modular product design combines components that have a high degree of interaction into a module (Bouchard et al., 2023).

Since both the total number of individual parts and the interactions between different parts can be reduced by modular design, scholars find a positive relation between modularity and decreased NPD lead time (Loch et al., 2003).

Although many contributions argue for these benefits, the number of empirical studies showing these relationships is limited (Danese and Filippini, 2013). A study claiming to be the first of its kind is Jacobs et al. (2007) which analyzes the impact of product modularity on costs, quality, flexibility, and time based on surveys in the US automotive industry. Strikingly, the analysis finds a positive effect on all four indicators. Concerning quality, modularity indirectly yields higher lot sizes per component, as creating variety by mixing and matching standardized parts ultimately allows for testing and refining the lower number of modules to a higher extent than individual parts would have been (Jacobs et al., 2007). Higher volumes also support the learning curve effects discussed in section 2.5.2.1. If issues arise concerning the product, they can be handled exclusively by changing a single module instead of the entire product, supporting both quality and shorter lead times (Feitzinger and Lee, 1997; Zarbi et al., 2024). Importantly, the study highlights positive modularity effects both with and without capitalizing on the option to parallelize processes (Jacobs et al., 2007). Similarly, the studies of Danese and Filippini (2013, 2010) find that modular design provides the strongest lead time lever when used in conjunction with supplier involvement and parallelized processes. Vickery et al. (2015), based on a survey of 93 companies, find a positive yet indirect relationship between product modularity and time-to-market, with manufacturing flexibility as the accelerating factor.

The manufacturing flexibility from modular product design gives companies the choice to outsource or internally develop individual modules independently, which affects both the degree of added value the company realizes through NPD and the cost and quality of the final product. The make-or-buy decision and its effects on product quality have been studied by Kalaignanam et al. (2017) for the US automotive industry. The authors find that the impact of internally producing or externally sourcing parts on the components and ultimately on the quality of the product is a complex one. Accordingly, decisions to buy are good for a short-term boost in quality, especially in environments of highly complex technologies. Make-decisions on the other hand allow the company to provide a higher quality to the customer in the long term which may even be amplified by feedback mechanisms allowing the company to learn from quality deficiencies (Kalaignanam et al., 2017). A superior integration effort of modular systems may arise due to inferiorly designed products in terms of their system performance (Ethiraj and Levinthal, 2004) or due to inefficient communication and integration processes (Sosa et al., 2004). It is important to note that an increased amount of parallelized processes and external sourcing raises coordination and reintegration efforts within the company, causing additional costs and potentially threatening overall quality (Danese and Filippini, 2013).

Besides, the flexible reuse of even highly performant components, combined with the possibility to postpone product differentiation, allows firms to reconcile high functionality and performance with short development lead times to a degree that integral architectures structurally preclude (Krishnan and Ulrich, 2001). Hence, to a certain degree, modular product design enables combining high product functionality and performance with low product development lead time. Danese and Filippini (2013) show that product modularity significantly reduces NPD time while simultaneously exerting a positive effect on product performance, indicating that the two objectives are not strictly substitutive under a modular regime. Worren et al. (2002) and Jacobs et al. (2007) provide comparable findings for the home appliance industry and across manufacturing sectors respectively. In a mathematical model, Wu et al. (2009) find that the tradeoff between market-timing proficiency and development lead time decreases as development team productivity increases, and using modularly designed components is an effective method for enhancing productivity. Ramachandran and Krishnan (2008) develop a mathematical model proving that the flexibility and upgradability gained through modularity allow companies to maintain competitive advantage through market timing without overshortening development. More broadly, modularity enables time reductions through parallelized development (Lau et al., 2007), component reusability (Hackl et al., 2020), and variety generation by mix and matching of components (Fixson, 2007).

Despite these advantages, modular components are argued to be more complex to develop initially, which is why modularity is often seen as a shift of time from product-specific development to overall product family development. The reduced time for testing activities with modular products may be held against their longer development time compared to integral products (Ulrich, 1995).

2.5.2.5 Tradeoff (e) – New Product Development (NPD) Lead Time and Total Cost (Direct and NPD Cost)

Increased market pressures demand companies to be fast in the market while managing their costs to stay in business sustainably (Afonso et al., 2008). Typically, decision-makers face a situation where time and costs cannot be optimized simultaneously. Several studies, e.g. Smith and Reinertsen (1995), argue for optimizing time-to-market over target costs, as time is often the higher lever on success. However, contributions arguing for the primacy of time typically focus on the fuzzy front end and imply through their employed penalty of delay that the overall cost gap may be resolved or minimized throughout the remaining development period (Hertenstein and Platt, 1999). Accordingly, Afonso et al. (2008) argue empirically that companies reach highest NPD success when they choose to optimize neither purely cost nor time-to-market but the best overall fit between the two.

Intuitively, one might assume a linear relationship between development time and costs since more time spent naturally increases development costs through allocated man-hours. However, the link between NPD costs and NPD lead time is more complex (Cankurtaran et al., 2013). There are several studies based on different methodologies such as case studies (Murmann, 1994), experiments (Gupta et al., 1992), interviews (Langerak et al., 2008), and analytical models (Bayus, 1997), that find a convex U-shaped relation between costs and development time during NPD (Langerak et al., 2010). The total cost curve represents the cumulative sum of the direct and overhead cost curves, and its U-shape stems from their combined time effects (Ulusoy and Hazır, 2021). Figure 13 schematically depicts the relation between NPD costs and lead time.

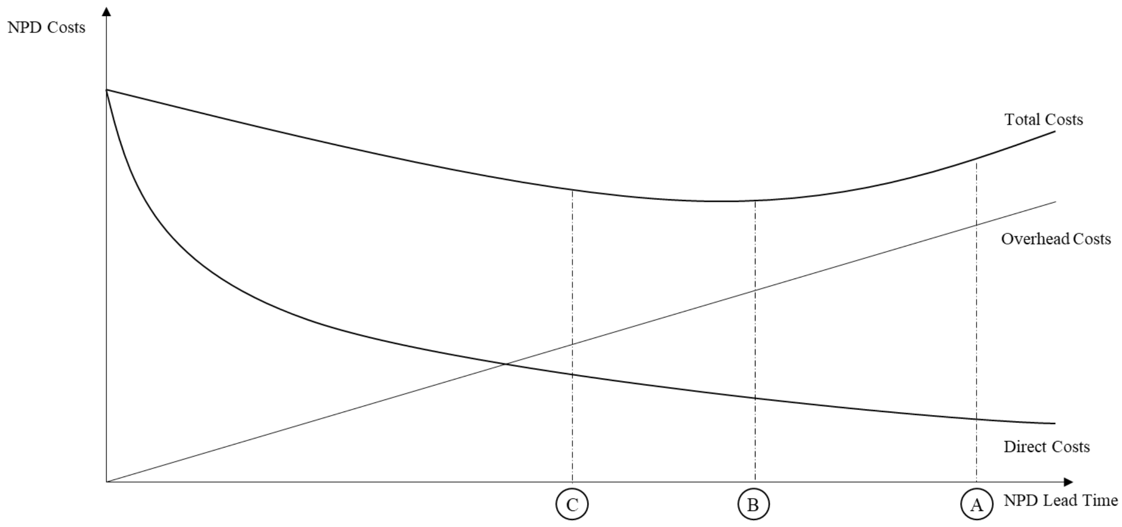

Figure 13 – Relation between New Product Development (NPD) Costs and Lead Time, based on Ulusoy and Hazır (2021, p. 143)

To explain this relation more elaborately, assume a fictional company aiming to reduce its NPD lead time, initially located on the right side of the U-curve at position A. At this stage, reducing development time simultaneously reduces total costs. However, once minimum total costs are reached at position B, further reducing development time to the target at position C ultimately increases costs again (Murmann, 1994).

Several reasons explain why cost and time reductions can initially be realized simultaneously between positions A and B. Decreased development time increases strategic flexibility, which may result in more efficient resource use and lower costs. Accordingly, Kandemir and Acur (2022) create a conceptual framework on strategic flexibility in NPD using European company data and identify shortened lead time as a crucial enabler for aligned decision-making. Second, fewer man-hours are allocatable to the project. Third, shorter lead time may minimize coordination effort and improve team cohesion. Fourth, there is a found indirect relation with employees' learning rates, hypothesized to rise with shorter processes. Accordingly, Lynn et al. (1999) empirically find that faster companies have better learning rates supported by clear NPD processes and a climate of organizational learning. Resource-wise, shortened development also lowers inventory levels, increases productivity, and leaves less room for peripheral spending (Cankurtaran et al., 2013).

Once minimum costs are reached, however, further reductions increase total costs. Graves (1989) reviews the literature and identifies four logical arguments for the convex relationship. First, further shortening leads to more work conducted in parallel or with fewer quality controls, causing worse processes and more rework. Companies may operate beyond their limits, leading to complex networks difficult to coordinate – especially when organizational processes are not adapted to the new speed and follow a functionally divided organization (Calantone and Di Benedetto, 2000). Second, the phenomenon of the mythical man-month by Brooks (2013) describes diminishing returns from additional staff due to extended coordination and training – a project of 240 work-days for one employee cannot be finished by 240 employees in one day (Graves, 1989). Third, as network theory implies, the lowest-effort actions are realized first, making further time reductions progressively more expensive. Lead time can only be compressed to the critical path minimum, requiring extensive work at these frontiers (Bayus, 1997). Fourth, more simultaneous activities increase the probability of failure, raising NPD costs (Graves, 1989). Additionally, speeding up activities may increase labor costs disproportionately through night shifts and overtime (Langerak et al., 2010). More in-depth reviews on the convex cost-time relationship are provided by Graves (1989), Langerak et al. (2010, 2008), and Cankurtaran et al. (2013) to which we refer interested readers.

Modularity Impact – Manufacturing Flexibility

Modular product design reduces the tradeoff between development costs and NPD lead time as it possesses several advantages influencing cost management and lead time. Davila and Wouters (2004) note that modular design allows NPD teams to design shared components outside the high-pressure development process, reducing the cost-increasing aspects of complexity and coordination effort under compressed lead times. Component reuse in multiple products reduces allocatable costs per product. When these components are pre-built or pre-designed, modular design enables cost reduction through scale and time reduction through parallelized processes (Hackl et al., 2020). Simplified reuse also reduces the need for entirely new development, minimizing costs and lead time simultaneously (Erixon, 1996). The case study of Ben Mahmoud-Jouini and Lenfle (2010) empirically illustrates how reused product platforms can be employed over several product generations to reduce the degree of convexity in the cost-time tradeoff. More explicitly, Nielsen et al. (2023) call for the development of reusable product platforms as a central means to overcome this tradeoff while employing a manufacturing systems perspective. Concerning agile methods, simulations by Watanabe and Ane (2004) claim a supporting influence of modular product design. Besides, modularity allows for relatively delaying the point of differentiation further down the development process, and it improves a company's strategic flexibility with positive impacts on both development costs and time (Wouters and Stadtherr, 2017).

2.6 Discussion and Conclusion

The purpose of this paper was to provide an overview of the financial tradeoffs that occur during the development of new interdependent products and to investigate the impact of product architecture decisions thereon. The literature review started with a collection of already existing reviews that concern the development of modular products and cost management methods regarding product architecture decisions. While there exist several related contributions, they typically discuss financial tradeoffs as one out of many distinct aspects to be considered during the individual phases of a product's lifecycle (Labro, 2004; Wouters and Stadtherr, 2017). Our integrative literature review places a tradeoff framework at the center of investigation and discusses financial tradeoffs both at the product level and at the level of product interdependence. While the different nodes of the tradeoff framework favor different decisions – e.g. optimizing direct costs at the expense of development costs or vice versa – it is the decision-maker's task to identify the best available solution. The best solution for an individual product may conflict with the best solution for the entire company. A corporate perspective therefore requires a centralized decision-making approach, as otherwise individual decision-makers on the product level first consider their own best available choice (local optimum), not being incentivized to look at the broader corporate picture (global optimum) (Israelsen and Jørgensen, 2011).

The previous section discussed financial tradeoffs at both levels and stressed the importance of a structured and ideally coordinated decision-making process when developing multiple products sharing components, modules, or platforms across a product family (Ramdas et al., 2003). We emphasized that traditional cost management approaches may not lead to optimal solutions for the commonality problem, since they neglect product interdependencies. The two levels of tradeoffs – the product-level tradeoff among revenue, functionality, and direct costs on one hand, and the tradeoffs arising from product interdependence involving overhead costs and lead time on the other – illustrate the complexity of decision-making during NPD in highly competitive markets. Companies operating in such markets must meet a diverse set of customer requirements, supplying product variety as large as necessary while keeping internal complexity as low as possible. Shifting the level of perspective – from the individual product to the portfolio – may lead to opposed decisions. Optimizing the direct costs of a product without considering portfolio effects may improve product-level profitability but likely yields an unfavorable state concerning development costs and ultimately an inferior total cost position (Wouters et al., 2016).

With this literature review, we answered two research question of which financial tradeoffs are present in the development of new products and what role do product architecture decisions in the form of modular product design play. We identified five tradeoffs that we discussed in a dedicated subsection of section 2.5. Besides, we found that the five definitional perspectives of Salvador (2007) – component commonality, component combinability, function binding, interface standardization, and loose coupling – yield modularity impacts that enable steering options in handling the individual tradeoffs. We discussed the individual tradeoffs in a detailed view per subsection and shed light on the economies of modularity that allow to combine scale and scope effects as well as we mentioned the dysfunctional status of assessing modularity impacts precisely to design the right incentives to overcome local optima in favor of a global optimum. Besides, we stressed that decision makers could choose in how much they want to use modular impacts to resolve the individual tradeoffs. This is determined by the volume as each degree of modularization – common components, shared modules, joint platforms – requires a certain volume to allocate the upfront development invest. At this point, we reemphasize that modularity is always a question of the extent, to which degree a modular architecture should be implemented (Lau et al., 2007).

We distinguished three kinds of modularity impacts that concern a company's variety management, manufacturing flexibility, and design options. Concerning variety management, we distinguished over-/underspecification, and complexity and variety. Over/underspecification arises once components are shared among multiple products, creating a mismatch between product-specific requirements and component properties that affects sales volume, price, functionality, and performance (Marzi, 2022). Complexity and variety describes the challenge that increased variety induces complexity costs that are hard to quantify, often underestimated, and characterized as delayed jump-fixed costs. Related to manufacturing flexibility, we highlighted the impacts of making or buying components, reusing components, late differentiation and parallelized development. Make or buy describes the architecture-enabled choice through standardization and clearly defined function-component relations to outsource or internally develop individual modules, affecting the cost, quality, and lead time of the final product. Reusing components describes using already developed components in new products to speed up development time and lower development cost. Late differentiations describes having highly similar products at the inside while differentiating them at the outside, which keeps options for differentiation high while maintaining a relatively low complexity. Parallelized development activities, that may be outsourced or conducted internally, enable companies to save time and optimize costs. Differentiation and similarity describe the tension between offering differentiated products to avoid cannibalization and employing common parts to reduce costs. Thereby, it captures the ability to create high external variety while keeping internal complexity low through strategies like mass customization enabled by standardized interfaces (Gebhardt et al., 2016).

As every study, this integrative literature review possesses some limitations. Foremost, we deliberately adopted an integrative rather than a systematic review approach, which prioritizes the synthesis of diverse perspectives into a conceptual framework over the exhaustive retrieval of all published evidence (Snyder, 2019). Although we complemented our database search with backward and forward citation tracking and manually added papers, our sample remains a curated rather than a complete representation of the relevant literature. Hence, relevant contributions may have been missed. Besides, our framework rests predominantly on analytical models and conceptual contributions. Empirical validation – particularly through observed financial outcomes – remains scarce across nearly all identified tradeoffs. Moreover, our framework treats the degree of modularization as a continuous design choice but does not specify how the optimal degree should be determined for a given firm or product family. This remains a case-specific decision (Boas et al., 2013) that requires firm-level financial data largely absent from the existing literature.

Future research is well-advised to address these limitations by combining empirical financial validation with cross-industry samples. The collected impacts of architecture decisions on financial tradeoffs during NPD stress the importance of getting the product architecture right for development activities while a solid quantifiable database is usually missing in practice. Beyond the substantive findings on tradeoffs and architecture impacts, this review reveals a severe imbalance between analytical modeling and empirical financial validation across all identified tradeoffs. Moreover, the empirical evidence that does exist is predominantly based on surveys measuring perceived effects rather than observed financial outcomes. Field studies that link actual cost, revenue, and lead-time data to architecture decisions – ideally through longitudinal designs that observe the same firm before and after architecture changes – would substantially advance the field. Besides, future research could empirically calibrate the existing analytical models using actual cost data from companies that have implemented modular architectures, thereby closing the identified validation gap. Critically, this evidence gap does not appear to be merely a research omission. Recent empirical work by Grønvald et al. (2026) demonstrates that even within companies, less than half of modularity-related effects possess sufficient data for accurate financial quantification. Nørgaard et al. (2025) trace this deficiency to a structural cause: traditional costing methods assess modularity effects at the product level while costs are incurred at the component and subsystem level, creating systematic inaccuracies that prevent informed architecture decisions. These findings, together with Jørgensen and Messner's (2010) observation that architecture-related cost decisions are made on intuition, suggest that the quantification gap reflects a genuine deficiency in corporate accounting systems rather than a mere absence of academic investigation.

Therefore, future work could examine how firms can build the cost-accounting capability needed to quantify modularity effects at the component and subsystem level.

3 Combining Target Costing, Cost-effectiveness, and Step Functions: A Pragmatic Approach to Deal with Cost Pressure and Tradeoffs

Abstract

Cost management techniques during new product development (NPD) implicitly assume that the cost gap between the actual and the allowed product costs is ultimately closable through activities such as target costing and value engineering. However, in case cost pressure is so significant that this assumption does not hold, tradeoffs between product properties are unavoidable. The objective of this study is to develop a practical approach in an optimization situation to identify a high-quality realizable product configuration meeting the cost target. This approach considers cost benchmarks, learning effects, and design limitations from commonality strategies. It also builds on cost-effectiveness of product enrichment activities: the extent of product improvement relative to additional direct cost.

Keywords: Target Costing; Value Engineering; Cost-effectiveness; Cost Management; Financial Tradeoffs; New Product Development

3.1 Introduction

New product development (NPD) is essential for companies to create innovative products and remain in business. Various departments – including marketing, sales, production, engineering, design, procurement, and finance – are typically involved (Elmogahzy, 2020). Ideally, all desired product properties can be realized, and the product achieves its desired financial return. Achieving this can be supported by target costing and value engineering (Iranmanesh and Thomson, 2008). Essential is to close the cost gap between actual and allowable cost (AC) (Ax et al., 2008). However, what happens if all activities to close the cost gap are insufficient and a cost gap remains (Thore Olsson et al., 2018)? Prior research provides limited guidance for such difficult yet plausible scenarios.

This paper focuses on complex, interdependent products under significant cost pressure and it proposes an extension of target costing that addresses several issues. First, it may be infeasible to find a design that realizes the full target product property profile (PPP) within the AC. We formulate the property enhancement decision as a constrained combinatorial optimization problem and present greedy procedures that use cost-effectiveness as the selection criterion. Second, breaking down the product level target costs onto the component level is in its industrial application more complex than captured in theory. Hence – in contrast to the traditional target costing process – we do not breakdown the product level target costs onto the component level but use an inverse logic of stepwise configuring realistic actual component costs into the final product. Third, interdependencies between product designs exist due to commonality strategies. Accordingly, our approach considers all components that are obliged due to such strategies. Furthermore, the relationship between product properties and customers' willingness to pay may be non-linear. Hence, we use a step-wise function to account for the significance of product property improvements.

In developing this approach, we collaborated with a company that is called European Car Corporation (ECC). Discussions with experts at ECC and involvement in the daily target costing activities at ECC provided the inspiration for the target costing extension that is investigated here. Throughout the paper, we illustrate the approach with a fictional yet realistic example for ECC.

The remainder of this paper is structured as follows. Section 3.2 presents a review of previous research as a motivation for the present study. In section 3.3, we present the research method as well as the research site where we conducted this methodological study. Afterward in section 3.4, we present a practically applicable approach building on target costing, value engineering, and cost-effectiveness aiming to maximally exploit the allowable cost target. It also illustrates the approach with a numerical example. As a greedy heuristic for a constrained combinatorial problem, the procedure typically produces a strong feasible configuration but does not guarantee global or local optimality. Its advantages lie in practical applicability, modest data requirements, and transparency of the selection logic (García, 2025; Peng et al., 2018; Wu and Hao, 2015). The discussion and conclusion follow in section 3.5.

3.2 Literature Review

3.2.1 Product Profile and Product Property Profile (PPP) during New Product Development (NPD)

The target product profile collects core information, requirements, and constraints that are important for the development of the product (Heitger, 2019). In the following, we adopt the definition of Albers et al. (2018, p. 255) which reads as follows.

"A product profile is a model of a number of benefits that makes the intended provider, customer and user benefits accessible for validation and explicitly specifies the solution space for the design of a product generation. The number of benefits will be understood as a set of products and services, which are offered with the purpose of being sold to a customer and to provide benefits for him directly or indirectly – e.g. for users taken into account by him or for his customers."

The product profile provides essential information for the product development process (PDP) as it defines the product's set of objectives and provides a reasoning for the development department that they deliver the right product. As such it is central to the initial target system formation as it translates strategic goals into an actionable, development-focused description. This summary creates a unified systemic understanding of the product generation by aligning the benefits for customers, users, and providers with the specific constraints of all stakeholders (Albers et al., 2018). Thereby, the degrees of freedom available in the design of the final product depend on the kind of the development project – ranging from developing a derivative product to an entirely new product family – and the available time-to-market (Heitger, 2019).

The more complex a product gets, the more diverse the kind of requirements a customer (implicitly) asks for. Kano (1984) originally distinguished three, a more recent extension distinguishes five distinct customer requirements: must-be, one-dimensional, attractive, indifferent, and reverse customer requirements (Bhardwaj et al., 2021). Table 6 illustrates these customer requirements using the simple example of a smartphone and Figure 14 schematically illustrates the customer requirements clustered based on a customer's (dis-)satisfaction level concerning the (un-)fulfilment of certain functionalities.

Table 6 – Example Customer Requirements, based on Bhardwaj et al. (2021, p. 10997)

Type of Customer Requirement	**Explanation**	**Example illustrated using a fictional Smartphone**
Must-be	Requirements that a customer expects to be fulfilled without explicitly articulating or being aware of. Hence, these characteristics could not increase the satisfaction and the utility the customer positively gains from the product. Must-be characteristics only become apparent once they are not or only insufficiently fulfilled which leads to a dissatisfied customer concerning his expectations.	• Make and answer phone calls • Send and receive text messages
One-dimensional	Requirements that are directly linked to the satisfaction of the customer. Hence the more they are fulfilled, the higher the satisfaction of the customer. In contrast, however, if these characteristics are not fulfilled, the customer will be dissatisfied by the offering.	• Display on time without need to recharge
Attractive	Requirements that are not expected by the customer. Their presence and fulfilment will increase the satisfaction of the customer. Their absence does not lead to any form of disappointment. These requirements are a delight for the customer and hence affect the satisfaction only in a positive manner.	• Rock-solid finished surface making protective cases obsolete
Indifferent	Requirements that do not influence the satisfaction of the customer at all. The customer neither values nor asks for their fulfilment and does not miss them in case of absence.	• Number of preinstalled ringtones
Reverse	Requirements that are negatively related to the satisfaction of the customer. In case these requirements are fulfilled the customer becomes less satisfied than in case these requirements remain unaddressed.	• Infringement of the user's privacy through recording and analyzing secretly captured information

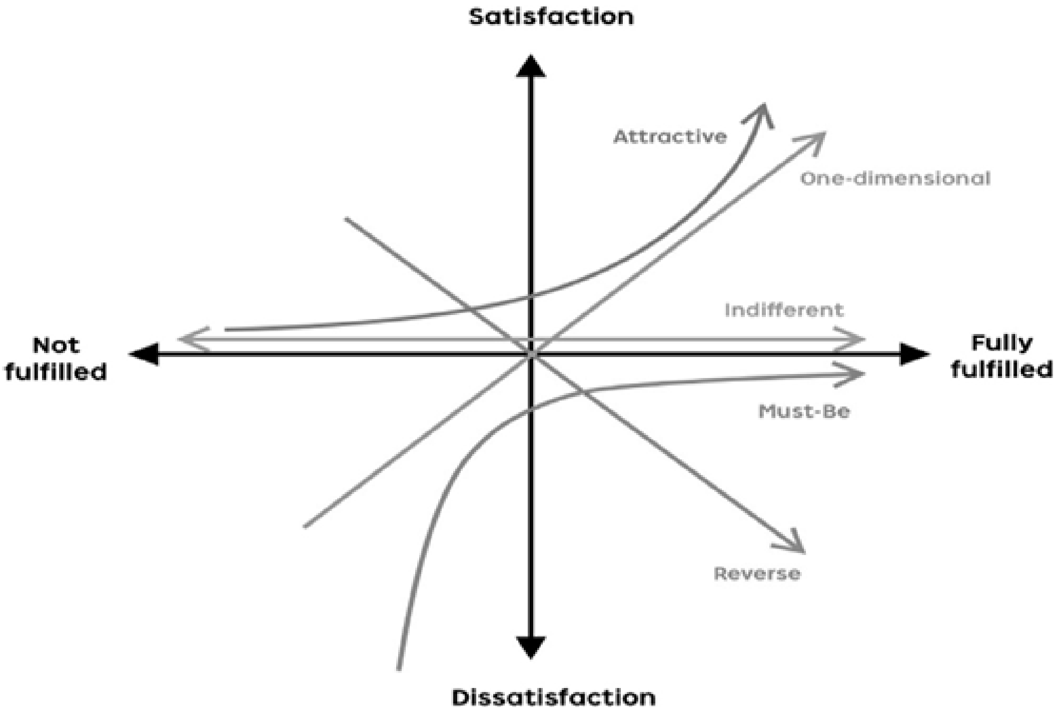

Figure 14 – Extended Model of Kano (1984), copied from Bhardwaj et al. (2021, p. 10997)

Within the initial target system formation, the property definition serves as a key phase resulting in the product property profile. This profile defines the product's character for the customer by combining various properties and their specific performance levels. Once manifested, the PPP ranks the importance of the individual properties and assigns a certain degree of importance to their fulfillment (Heitger, 2019). Within the automotive industry, the core properties are first made tangible in net diagrams where they mark a dimension among which the new and the competitive products are compared to each other (Schockenhoff et al., 2020). For complex products, as for example in the automotive industry, the properties are compared on different levels. A top-level view typically uses net diagrams whereas a more detailed sub-system view uses polarity diagrams or property-specific one-pagers that precisely describe the target for the individual properties on a detailed sublevel and provide benchmark information upon it. (Braess et al., 2013).

Figure 15 summarizes the various levels of the PPP exemplarily. The graphic illustrates, how the fictional target product property C is broken down into more granular levels[1].

[1] More Detailed Information is provided by Heitger (2019) or Braess et al. (2013).

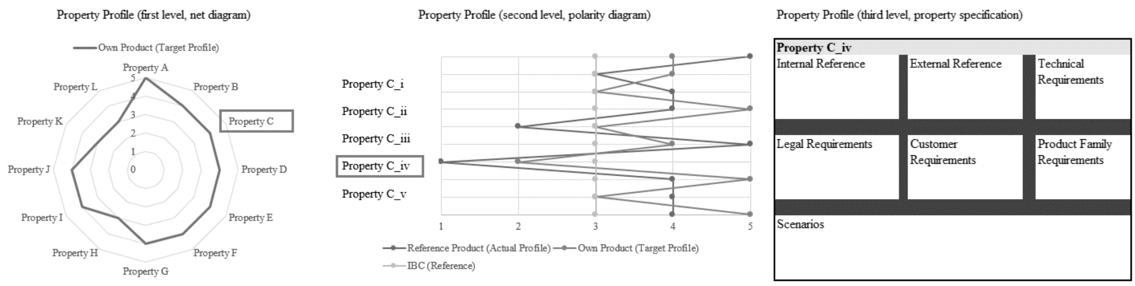

Figure 15 – Product Property Profile (PPP) on Different Levels

The product's positioning in the marketplace aims to differentiate it from competitor products in an empty slot in the market, which positively influences consumer perception and builds a competitive advantage (Saqib, 2021). Ultimately, the PPP clarifies the required actions to develop a product that matches its designated positioning (Stöber et al., 2010).

3.2.2 Cost Management during New Product Development (NPD)

Figure 16 summarizes well-known cost management methods during NPD and production.

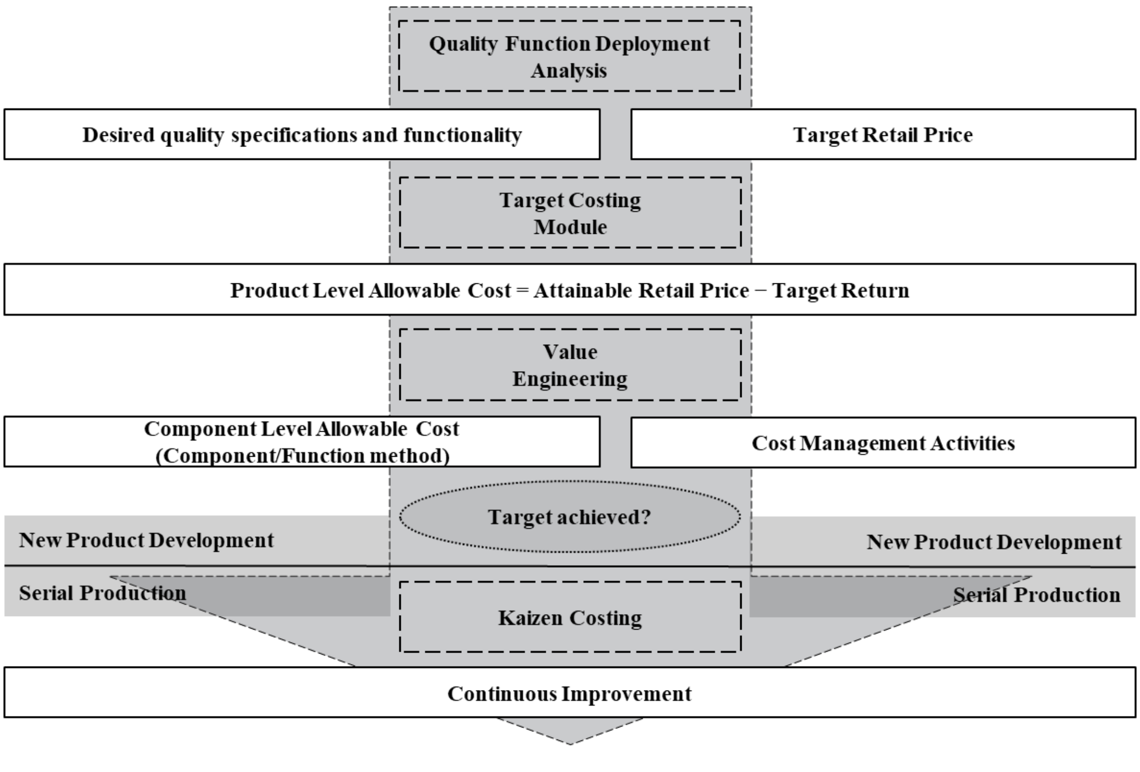

Figure 16 – Cost Management Activities during New Product Development (NPD) and Production, adapted from Zengin and Ada (2010, p. 5596) and Ellram (2002, p. 236)

Central for cost management during NPD is target costing, which is often combined with quality function deployment (QFD) (Durga Prasad et al., 2014; Zengin and Ada, 2010) and value engineering (Ax et al., 2008; Cooper and Slagmulder, 2017; Kumar, 2014; Setti et al., 2021). QFD thereby characterizes a tool to stepwise translate desires from customers into product design characteristics, followed by parts characteristics, and ultimately production requirements. Value engineering is a proactive, function-oriented systematic approach applied predominantly during the conceptual and early design development stages of new products (Setti et al., 2021). Target costing is a reverse costing methodology that is based on the attainable market price and desired return in order to compute a product target cost (PTC). The PTC is usually set equal to the allowable cost (AC) that are defined as the maximum cost level securing a desired product level target return (TR) based on its attainable retail price (ARP) on the market (Glaser, 2002; Kumar, 2014).

$$PTC := AC = ARP - TR * ARP = ARP * (1 - TR)$$

During NPD, the cost of the current product design is estimated, which is also called drifting cost (DR), to check whether the product target cost will be achieved. Comparing the cost estimate with the PTC defines the cost gap (CG) that remains to be closed during the further PDP (Ax et al., 2008; Kajüter, 2013).

$$CG = DR - PTC$$

The costs need to be broken down into cost targets for subassemblies, functions, and cost items to steer development activities and negotiate component-level purchase prices with suppliers. Companies could employ the function-oriented or the component allocation method. Whereas the former one allocates costs to the functions of a product which are then fulfilled by its components, the component allocation method directly allocates costs to its subassemblies and typically assumes a cost structure similar to existing products (Everaert et al., 2006). The component-level cost targets form the basis for cost management activities aiming to close the gap between projected actual costs and allowable target costs for components (Cooper and Slagmulder, 2017).

3.2.3 Limitations of Target Costing

Considerable research has addressed the adoption of target costing in different sectors (Dekker and Smidt, 2003; Ellram, 2006; Yazdifar and Askarany, 2012), organizational aspects of target costing (Afonso et al., 2008), as well as methodological extensions (Filomena et al., 2009; Kee, 2010; Stadtherr and Wouters, 2021). Still, fitting the target costing approach to specific organizational contexts, such as the automotive industry (Monden and Hamada, 1991), is challenging. Besides, there exist dedicated summaries enumerating areas of uncharted research territories within the application of target costing during NPD (Ahn et al., 2018; Ansari et al., 2006; Davila and Wouters, 2004). We will discuss a number of limitations of target costing that motivate the proposed extension that is present in the current paper. Figure 17 denotes these areas as well as our solution approach briefly.

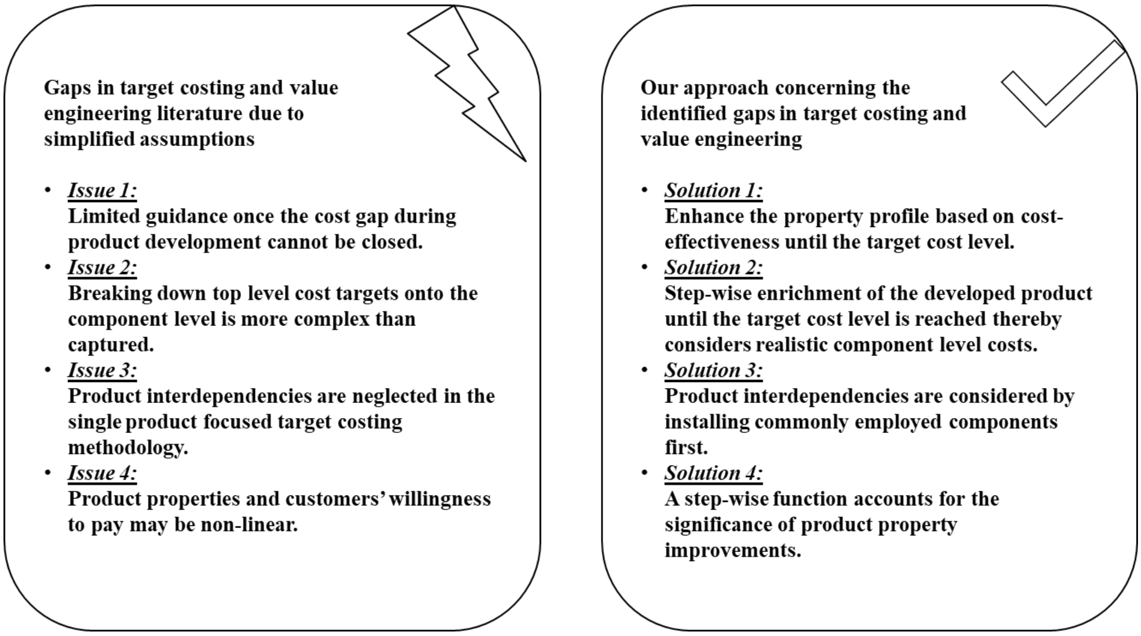

Figure 17 – Overview of Target Costing Limitations

First, more work is needed on situations in which it is not feasible to develop a product that realizes the full set of product properties within the allowable cost limit. Prior research on target costing and value engineering addresses this challenge in numerous ways. Becker and Gaivoronski (2018) present incremental target costing where information about customer requirements and target costs is stepwise validated as the uncertainty diminishes over time. The optimization approach assumes that the desired product properties can be realized at the allowable cost. Some studies provide case-specific solutions to achieve the target costs, such as the engine starter example of Ibusuki and Kaminski (2007) or the hydrostatic unit of Zengin and Ada (2010). Other studies assume that not all product properties may be achievable at the AC and present approaches that optimize customer satisfaction under the constraint of an allowable cost, e.g. as in Jariri and Zegordi (2008). Newer studies also incorporate multi-objective optimization to attain the maximum customer satisfaction and lowest possible cost simultaneously (Durga Prasad et al., 2014). Bock and Pütz (2017) propose a dynamic programming approach but mention that such complex optimization is only limitedly applicable in practice. Some studies account for uncertainty by applying fuzzy logic (Gandhinathan et al., 2004). While these approaches provide important extensions of target costing, they typically concern a single component instead of an entire product, and they require much data that may not always be available. More broadly, decision-making to adjust product properties and to make tradeoffs under cost pressure during product development involves many different considerations (Thore Olsson et al., 2018).

Second, the method for breaking down target costs of a product level on the component level can be more complex than most approaches, like the predominant function or component method, consider (Ahn et al., 2018; Kajüter, 2013). The function method is market oriented and translates a customer's willingness to pay into a company's allowable cost per component. The relative weight of the functions is measured by conjoint analysis, and weighted by function-component matrices (Homburg et al., 2021; Horváth, et al., 1993). Thereby, a linear relationship between costs and customer utility is assumed, which is only given for so-called one-dimensional customer requirements as of the model from Kano (1984). A limited number of studies provides an extension to the baseline function method applicable for complex products (Becker and Gaivoronski, 2018; Homburg et al., 2021; Hoque et al., 2005; Rösler, 1996; Schaaf, 1999; Schulte-Henke, 2008).

The approach of Rösler (1996) is to first create a minimum product fulfilling the basic requirements (the must-be qualities) in a cost-effective way and to reserve an innovation budget for covering the attractive qualities. This budget is distributed based on the customer's desires. Schaaf (1999) adopted a similar approach and proposed an iterative heuristic to distribute the overall derived target costs. Schulte-Henke (2008) builds its extension of target costing on the work of Rösler (1996) and criticizes that this is unable to capture the entire magnitude of customer requirements for complex products as it conceives required product functionalities only from a corporate perspective while neglecting a customer's point of view (Schulte-Henke, 2008). To overcome this issue Schulte-Henke proposes the use of expert-based degrees of importance which express the importance of a product property from the customer's perspective.

Hoque et al. (2005) propose an approach that combines the perspectives of the customer, the designers, and the estimated costs from an engineering perspective. They assign individual weights based on these three perspectives to break down the product level target costs on the component level. Ultimately, this approach yields a minimization function deemed to assimilate the three weights to an overarching one. Becker and Gaivoronski (2018) provide an extension to the model of Hoque et al. (2005) by shifting the focus toward optimization under uncertainty. They argue that the relationship between costs and product attributes is not linear or fixed and introduce a link function z that matches product costs and attributes considering the impacts on demand. This leads to an efficient frontier of potential product configurations that product managers can select from. Unlike the static targets in earlier models, Becker and Gaivoronski (2018) utilize this link function to visualize the optimal tradeoffs – for any given cost, the frontier shows the maximum achievable quality and vice versa.

Homburg et al. (2021) is a very rare example of a methodological extension of the traditional target costing methodology to derive component level target costs. Hence, we present their extension rather exhaustively. Whereas traditional target costing implies the independence of customer preferences and therefore uses additive utility functions, the authors argue that this becomes only true once basic functionalities of the product are guaranteed. For example, installing the best available engine on the market into a truck without wheels does not improve the value of the truck as its basic functionality of driving cannot be fulfilled without wheels. Therefore, adding up customer utilities and benefits related to components becomes only reasonable once the basic functionalities are fulfilled. Hence, Homburg et al. (2021) use a two-stage cost assignment approach and calculate the DR and AC twice, once for a minimum variant and once for a desired product variant. Table 7 denotes the mathematical extensions that Homburg et al. (2021) present.

Table 7 – Comparison Traditional Target Costing and the Modification of Homburg et al. (2021)

Traditional Target Costing as of Glaser (2002)	$$PTC \coloneqq AC = ARP * (1 - TR)$$ $$DR = CG + PTC$$
Modified Target Costing approach by Homburg et al. (2021)	Minimum Product Configuration: $$\underline{AC} = \underline{ARP} * (1 - \underline{TR})$$ $$\underline{DR} = \underline{CG} + \underline{PTC}$$ Desired Product Configuration: $$\overline{AC} = \overline{ARP} * (1 - \overline{TR})$$ $$\overline{DR} = \overline{CG} + \overline{PTC}$$ Referring to traditional target costing, the following relation applies: - Traditional Target Costing $AC \coloneqq \overline{AC}$ Notation of Homburg et al. (2021) - Traditional Target Costing $DR \coloneqq \overline{DR}$ Notation of Homburg et al. (2021) Addition of Homburg et al. (2021): - Modified Allowable Cost: $AC^{mod} = \overline{AC} - \underline{AC}$ - Modified Drifting Cost: $DR^{mod} = \overline{DR} - \underline{AC}$ with: $$\overline{DR} \leq \overline{AC}$$

The approach to split the allowable and drifting cost is best illustrated by the following simple example of Homburg et al. (2021) denoted in Table 8. The example illustrates the calculation of the component specific cost gap using the interior of a fictive car. Thereby traditional target costing – e.g. as of Glaser (2002) – and the modified approach of Homburg et al. (2021) lead to a distinctive component specific cost gap that remains to be closed by cost management activities. The overall cost gap on a product level remains constant for both approaches.

Table 8 – Example from Homburg et al. (2021, pp. 852–856)

Variable	**Example**	**Mathematics Traditional Target Costing as of Glaser (2002)**	**Mathematics Modified Target Costing by Homburg et al.** (2021)
Attainable retail price desired product configuration	30,385.00 EUR	ARP	$\overline{ARP}$
Target return desired product configuration	35%	TR	$\overline{TR}$
Allowable cost desired product configuration	19,750.00 EUR	$PTC := AC = ARP * (1 - TR)$	$\overline{PTC} := \overline{AC} = \overline{ARP} * (1 - \overline{TR})$
Cost gap desired product configuration	6,077.25 EUR	CG	$\overline{CG}$
Drifting cost desired product configuration	25,827.25 EUR	$DR = CG + PTC$	$\overline{DR} = \overline{CG} + \overline{PTC}$
Attainable retail price minimum product configuration	10,475.00 EUR	Not considered	$\underline{ARP}$
Target return minimum product configuration	30%	Not considered	$\underline{TR}$
Allowable cost minimum product configuration	7,332.00 EUR	Not considered	$\underline{AC} = \underline{ARP} * (1 - \underline{TR})$
Cost gap minimum product configuration	2,619.25 EUR	Not considered	$\underline{CG}$
Drifting cost minimum product configuration	9,951.25 EUR	Not considered	$\underline{DR} = \underline{CG} + \underline{PTC}$
Modified allowable cost	12,418.00 EUR	Not considered	$AC^{mod} = \overline{AC} - \underline{AC}$
Modified drifting cost	18,495.00 EUR	Not considered	$DR^{mod} = \overline{DR} - \underline{AC}$
Minimum allowable cost to minimum drift-ing cost ratio	74%	Not considered	$\frac{\underline{AC}}{\underline{DC}}$
Relative utility of interior (exemplary component)	23%	$U_{Interior}$ Coming from Function-Component Matrix	$U_{Interior}$ Coming from Function-Component Matrix
Drifting cost of interior minimum product configuration	1,500.00 EUR	Not considered	$\underline{DR}_{Interior}$, estimated
Allowable cost of interior minimum product configuration	1,105.19 EUR	Not considered	$\underline{AC}_{Interior} = \underline{DR}_{Interior} * \frac{\underline{AC}}{\underline{DC}}$
Drifting cost of interior desired product configuration	5,000.00 EUR	$DR_{Interior}$	$\overline{DR_{Interior}}$
Allowable cost of interior desired product configuration	3,823.48 EUR	$AC_{Interior}$	Not considered
Modified drifting cost of interior desired product configuration	3,894.81 EUR	Not considered	$\overline{DR^{mod}_{Interior}} = \overline{DR_{Interior}} - \underline{AC}_{Interior}$
Modified allowable cost of interior desired product configuration	2,856.14 EUR	Not considered	$\overline{AC^{mod}_{Interior}} = AC^{mod} * U_{Interior}$
Cost gap of interior desired product configuration	1,176.52 EUR	$CG_{Interior} = DR_{Interior} - AC_{Interior}$	Not considered
Modified cost gap of interior desired product configuration	1,038.67 EUR	Not considered	$\overline{CG^{mod}_{Interior}} = \overline{DR^{mod}_{Interior}} - \overline{AC^{mod}_{Interior}}$

Due to the limitations mentioned above, companies producing complex products prefer the component method (Mihm, 2010). The component method directly breaks down the costs on the component level and uses the cost structures of similar products. It considers customer requirements only implicitly and requires a similar product as input data (Kajüter, 2013).

Filomena et al. (2009) contribute an extension to the component method to directly account for distinctive property representations of existing parts as well as analogously developed components. Their approach consists of a four stepped process that considers the potentially increased retail price due to property improvements. An alternative approach that does not breakdown the costs in the classical sense but uses a scenario-based bottom up approach is the contribution of Laschka (2021). The method uses scenario technique and cost benchmarks to reach product level target costs.

Third, more work is needed on target costing when product designs are interdependent. Target costing aims at retrieving the allowable direct costs, in most cases direct costs, of a single product and neglects product interdependencies as well as other cost types. However, interdependencies between product designs exist due to commonality strategies. Stadtherr and Wouters (2021) provide an extension of target costing to account for overhead costs. Ortelbach (2005) addresses target costing when several product variants for multiple target markets are designed and sold at different price levels, which leads to diverging allowable cost for the same components. Götze and Linke (2008) stress that there is no general solution once commonly employed components should be considered in target costing. They propose ways for dealing with diverging allowable cost of a component because it is used in several products that have different prices and margins. Israelsen and Jørgensen (2011) address adjustments of target costing to stimulate optimal component sharing decisions in product development. Kee and Matherly (2013) provide a numeric example to stress the importance of coordinating decisions when product interdependencies are present and suggest implementing target costing at the portfolio level. Goswami et al. (2017) provide an example for product line design of interdependent products. They use an objective function that maximizes product premium prices while minimizing product manufacturing costs, assuming that more functionalities automatically boost the overall sales and the customer's willingness to pay.

Fourth, property improvements and customer responses are not necessarily linked linearly. An example for such a simplified linear assumption is Goswami et al. (2017) or Yadav and Goel (2008). Roy et al. (2008) use two sets of cost functions, whereof one assumes a binary link as the component is either installed or not and the second one depends on the degree up to which the property is fulfilled. Accordingly, the authors acknowledge different degrees of relationships between property fulfilment and costs in an optimization setting.

The current chapter provides an extension of target costing that offers a pragmatic approach to adjust the product property profile within the limits of AC. It uses a bottom-up based enrichment process and thereby overcomes arbitrary component level targets. Due to the use of common parts for cost management purposes, it also addresses product interdependencies. Furthermore, our approach incorporates a non-linear relationship between product property improvements and customer responses.

3.3 Research Method and Research Site

3.3.1 Action Research Approach

This study follows an action research design (Checkland and Holwell, 1998; Hameri and Paatela, 2005). Action research is an emergent inquiry process that simultaneously solves real organizational problems and contributes to scientific knowledge (Formentini and Romano, 2011). We conducted our research as external researchers at an automotive original equipment manufacturer (OEM) company, referred to as European Car Corporation (ECC), where we accompanied the NPD process over a three-year period (Jönsson and Lukka, 2006; Lukka and Wouters, 2022).

Our research follows the FMA framework proposed by Checkland and Holwell (1998). The framework of ideas (F) emerged from three sources, i.e. discussions with ECC experts, our involvement in daily target costing activities, and our review of the literature on NPD, target costing, and value engineering. Through this engagement, we identified a decision problem that – we conjecture – extends beyond ECC to any company developing complex, interdependent products under significant cost pressure: how to distribute allowable cost across product-specific and commonly employed components when the cost gap cannot be fully closed through conventional cost management activities. The methodology (M) is our proposed approach, which combines target costing, value engineering, and cost-effectiveness analysis to address this problem. The area of concern (A) is ECC, where the approach was developed and applied.

The methodology was developed iteratively in conjuncture with ECC practitioners and is demonstrated through a fictional yet realistic numerical example in section 3.4. All data are disguised and simplified for confidentiality reasons. We acknowledge that this example demonstrates the feasibility and internal logic of the approach rather than providing full empirical validation – a limitation inherent to the early-stage development of new methodological tools in applied settings (Formentini and Romano, 2011). Detailed formulas and calculations are presented in section 3.4.

3.3.2 European Car Corporation (ECC) and its Product Architecture

We conduct our research in cooperation with ECC that sells its cars worldwide. A modern-day passenger car, like those sold by ECC, is highly complex with a bill of materials listing roughly 2,000 to 2,500 parts depending on the drivetrain. The number of configuration opportunities can reach astronomical levels as Hu et al. (2008) reports 10^{17} theoretically possible variants of configuring a BMW 7 series.

At ECC, a vehicle is composed of three categories of parts: hat parts, modules, and platform parts. Hat parts are product-specific, externally visible components that define the product's distinctive appearance, such as the body shape (Stadtherr and Wouters, 2021). Modules are shared building blocks employed across multiple products. We adapt the definition of Jiao and Tseng (2000, p. 469) for our purposes. Hence, we understand modules as follows.

"A module is a physical or conceptual group of components designed to uniquely fulfill an underlying core functionality of the fully built up product while allowing to be employed within a multitude of similar products."

Each module type defines a functionality (e.g. the engine enables propulsion), while module variants differ in how they fulfill it (e.g. an engine producing 200 horsepower affects driving dynamics through acceleration and top speed). A modular toolkit comprises all module types and their variants available for a series of related products. We denote individual modules as $M_{m,v}$, where the indexed m identifies the module type and the indexed v specifies the module variant.

$$m, v \in \mathrm{N}$$

$$\sum m = M$$

$$\sum v = V$$

The product platform is the largest shared module and defines the common structure – at ECC, this includes the floor structure, wheelbase, and axle track width (Jiao et al., 2007). For our understanding, we define product platforms as of Meyer and Lehnerd (1997, p. 39) which reads as follows.

"A product platform is a set of subsystems and interfaces that form a common structure from which a stream of derivative products can be efficiently developed and produced"

Figure 18 schematically summarizes ECC's product architecture.

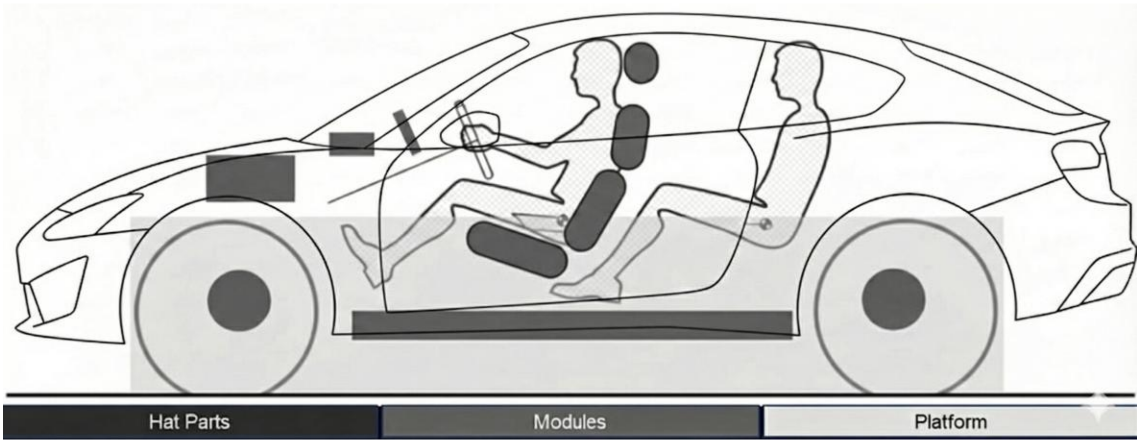

Figure 18 – Overview of the Product Architecture at European Car Corporation (ECC) – Disguised Image copied from Google (2025)

The cost structure of a typical product of ECC is also complex and characterized by a huge share of direct material costs relative to the total cost level. Accordingly, direct material costs account for approximately 60% of total product costs at ECC – roughly one-third of the retail price. Of these, about two-thirds are attributable to modules and the platform (shared across the product family and sister brands), while one-third covers non-modular parts. Shared components thus represent approximately 40% of total costs, underscoring the importance of managing them from the earliest development stages.

Figure 19 illustrates ECC's product cost structure using disguised data.

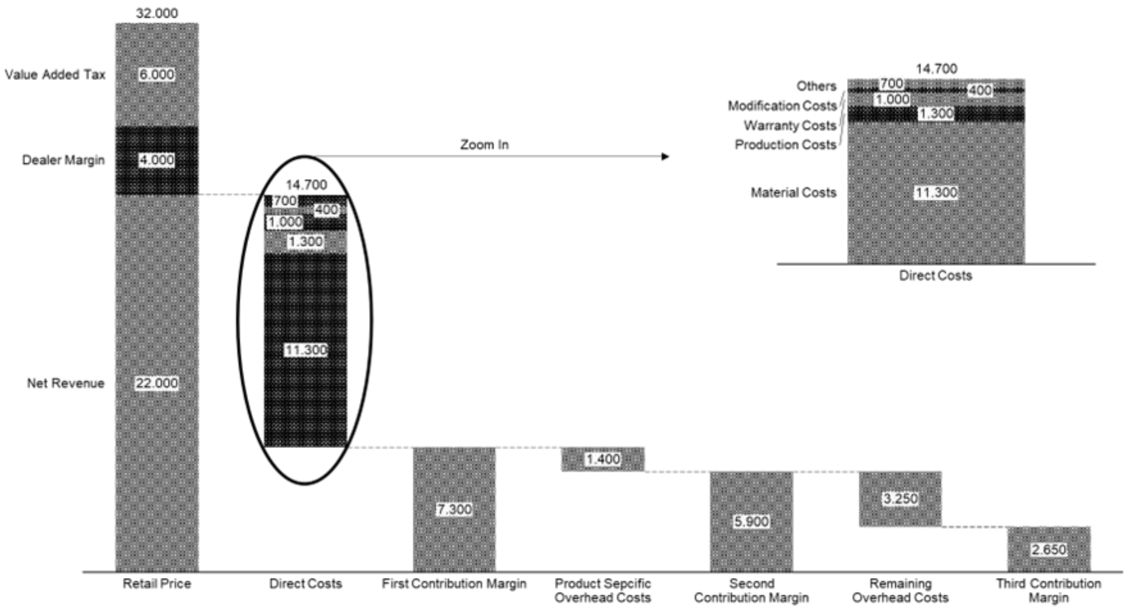

Figure 19 – Overview of the Product Cost Structure at European Car Corporation (ECC) – Disguised Data

We assess ECC's business case at the product family level. A product family comprises variants that share the same module types but differ in at least one value-affecting property (Jiao et al., 2007; Jonas, 2013; Krause and Gebhardt, 2018). We treat the terms "product family" and "product line" as synonymous (Jiao et al., 2007) and denote product families as P_i , where the index i specifies the exact product family.

$$i \in \mathrm{N}$$

$$\sum i = I$$

A specific product configuration is defined by three additional dimensions: sales region s, trim levels t, and product variants u. Accordingly, $P_{i,t,s,u}$ refers to the u^{th} product variant of the product line i configured in trim level t to be sold in the sales region s – for instance, a sedan (u) variant of model A (i) in top trim (t) for the European market (s).

$$s, t, u \in \mathrm{N}$$

$$\sum s = S$$

$$\sum t = T$$

$$\sum u = U$$

Figure 20 illustrates this configurational complexity.

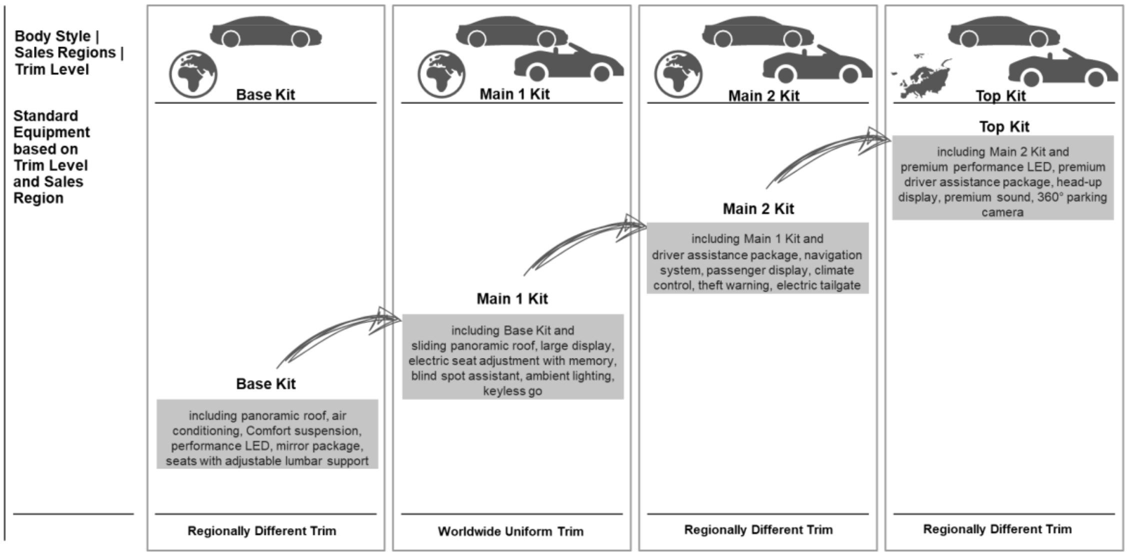

Figure 20 – Overview of the Product Complexity at European Car Corporation (ECC) – Disguised Image

Module commonality arises when different product lines employ the same module variant. This does not require full overlap across product lines – commonality can occur selectively. Higher-configured versions of a lower-segment product may share modules with entry-level versions of a higher-segment product, creating cross-product interdependencies that the cost management approach must account for.

3.4 Proposed Extension of Target Costing

This section presents an extension of target costing that addresses the issues outlined above. As introduced earlier, this approach was developed in collaboration with ECC. The numbers as well as the PPP and its stepwise enhancement are fictional due to confidentiality but still in a realistic order of magnitude.

We formulate the enrichment decision as a constrained combinatorial optimization problem – selecting among discrete enrichment activities subject to the allowable cost (budget), property-level step thresholds, and target-level constraints – and propose a greedy heuristic to address it (Kellerer et al., 2004). The proposed approach is shown in Figure 21. Initially, the target PPP, the attainable retail price (ARP), and the allowable cost (AC) are defined, as this is usually done in target costing. The proposed approach then considers three product configuration steps. Instead of reducing the product properties to achieve the target costs via a series of cost management activities, we propose to systematically “enrich” the product to get closer to the target PPP within the allowable financial target. Building on a predecessor product and its cost base, the first configuration step considers economies of learning (EoL), economies of efficiency (EoE), cost benchmarks, and legal requirements to configure the segment-specific minimum product (SSMP). The next configuration step considers required components due to commonality strategies to configure the segment-specific enrichment product (SSEP). In the final configuration step, further technical product enrichment activities are selected until no further activity can be feasibly added under the defined constraints. These enrichment activities are selected based on cost-effectiveness: how much a particular enrichment activity helps to get closer to the target PPP relative to the additional product cost of that activity. The final product configuration is called best of budget product (BoBP).

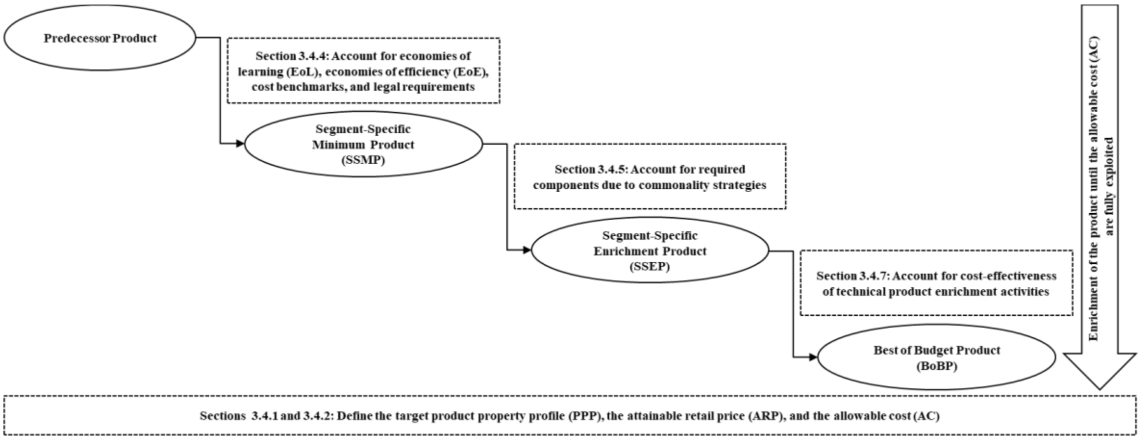

Figure 21 – Overview of the Proposed Approach

3.4.1 Target Product Property Profile (PPP)

The target levels for the product properties are defined relative to a set of competitor products that serve as a benchmark. Specifically, target levels are defined in discrete steps relative to the expected properties of these competitor products. Particular levels of property points (PP) correspond to the discrete property levels, which are indicated in Table 9 for the example of the property driving dynamics.

Table 9 – Example of Target Property Levels for Driving Dynamics (D) – Disguised Data

Target Property Level	Explanation	Rank (Target PPP)	Required Property Points (PP)
Best In Class (BIC)	Better than all competitor products	5	≥ 301
Top (TOP)	Exactly as good as the best product in the set of competitor products	4	300
In Best Class (IBC)	In-between the worst and the best product in the set of competitor products	3	91–299
Last In Class (LIC)	Exactly as good as the worst product in the set of competitor products	2	90
Under Last In Class (ULIC)	Worse than all competitor products	1	0–89

A particular product configuration can be scored (this can be done at any stage of product development) in terms of the number of reached property points (RPP) for each product property. For example, driving dynamics (first level of the PPP) could be broken down into sub-properties such as longitudinal and transverse dynamics (second level of the PPP), which could as such be measured by the car's top speed or acceleration. On this second level, the RPP can be assessed. This can be expressed on various scales, such as binary, rank-based, or continuous[2].

A key idea for the proposed approach is that product improvements are only significant in discrete steps, namely when additional PP are enough to reach the next target property level. Customers will recognize such discrete "jumps" in product properties in comparison to competitor products. In contrast, improvements still below the next target property level are modeled as insignificant, as they remain unnoticed by the customer. The property point increment (PPI_{Pr}) of property Pr is defined as the gap between the currently RPP (before any additional product enrichment activities) and the number of PP required to reach the next higher property level. For example, if the current level of PP would be 229, then the next higher target property level would require 300 PP (TOP, in the example), then the required increment is 71.

$$PPI_{Pr} = Min(PP_{Rank\ i+1}) - PP_{PR,before\ Technical\ Enrichment\ Activity}$$

Hence, all technical enrichment activities discussed afterwards are aimed at reaching a higher property level. The implied utility function of the customer and the product's quality is therefore a *step function* that reaches the next level once the improvements are bigger than the PPI_{Pr}. So instead of assuming a linear relationship between resources spent, product improvements and customer satisfaction, this approach builds on ideas in the target costing literature about having customer requirements at various levels. For example, Yadav and Goel (2008) define product properties and cost targets at three levels, i.e. vehicle, system, and subsystem level, and they consider the Kano model categories of product properties: must-be, one-dimensional, and attractive properties. Homburg et al. (2021) differentiate between product properties and costs necessary to realize a minimum product variant and costs necessary to implement additional functionalities.

3.4.2 Multi-Stage Target Costing at the Product Level

The approach uses one aggregated ARP per product line, even though the product is sold at many different prices due to different trim levels (such as a base version and a top version, typically differentiated by costly modules like engines, or battery stacks), multiple sales regions s (e.g. Germany, USA, China), and various product variants (sedan, station wagon, coupe, etc.). The aggregated ARP leads to one overall AC per product line. Otherwise, an individual ARP and AC per individual configuration would need to be calculated. For example, simply having five trim levels, five sales regions, and four product variants would already yield 100 different trim-region-variant combinations.

The aggregation of the individual ARPs follows a three-step approach using the individual sales volumes (SV) as the weighting factor. First, all region and trim specific $ARP_{t,s,u}$ are aggregated to an $ARP_{u,s}$ per sales region.

[2] An example for the binary scale would be the installation of LED headlights (yes/no). An example for the rank-based scale would be the configuration of foldable seats, with three ranks: fixed (least desirable), 60:40 dividable seats, and 50:50 dividable seats (most desirable). An example for the continuous scale would be the top-speed, whereby, for example, a S-shaped relationship between increased speed and added customer utility could be assumed.

$$ARP_{u,s} = \sum_{t=1}^{T} ARP_{\mathrm{t,s,u}} * \frac{SV_{\mathrm{t,s,u}}}{\sum_{t=1}^{T} SV_{\mathrm{t,s,u}}}$$

Next, the sales region specific $ARP_{u,s}$ is aggregated on a product variant level to state an ARP_u per product variant.

$$ARP_u = \sum_{s=1}^{S} ARP_{u,s} * \frac{SV_{u,s}}{\sum_{s=1}^{S} SV_{u,s}}$$

Finally, the product variant specific ARP_u are again volume-weighted to derive the product line ARP.

$$ARP = \sum_{u=1}^{U} ARP_u * \frac{SV_u}{\sum_{u=1}^{U} SV_u}$$

The AC is derived from the ARP in several steps. Local taxes, import and export fees, as well as dealer margins are deducted from the ARP to arrive at the net revenue (NR). After also subtracting the direct costs (DC) from the NR, we get the contribution margin (CM).

$$NR = ARP - (Dealer\ Margin + Taxes + Import\ and\ Export\ Fees)$$

$$CM = NR - DC$$

Finally, the financial return (R) is measured as the contribution margin relative to the net revenue:

$$R = \frac{CM}{NR}$$

The TR, i.e. the target for this financial return, is defined by the management accounting department and is the basis for arriving at the target for the CM, which leads to the cost target AC.

$$TR = f(NR)$$

$$AC = NR * (1 - TR)$$

$$AC = ARP * (1 - TR)^{3}$$

3.4.3 Numerical Example Part I

The target PPP of our example is shown in Table 10. This includes five distinct product properties: Suitability for everyday use (S), driving dynamics (D), comfort (C), quality (Q), and environmental compatibility & sustainability (E). The calculation of the AC is derived in Table 11.

[3] Assuming there are no dealer margins, taxes, import or export fees to be considered.

Table 10 – Example Target Product Property Profile (PPP) – Disguised Data

Property	ULIC	LIC	IBC	TOP	BIC
Suitability for everyday use (S)	0–89	90	91−189	**190***	≥ 191
Driving dynamics (D)	0–89	90	91−299	**300***	≥ 301
Comfort (C)	0–9	10	**11−99***	100	≥ 101
Quality (Q)	0–69	70	71−229	230	**≥ 231***
Environmental compatibility & sustainability (E)	0–84	85	86−144	145	**≥ 146***

Note: Target property levels indicated bold and measured in property points (PP)

Table 11 – Example Allowable Cost (AC) – Disguised Data

Row	Variable	Abbreviation	Example Value	Source / Formula
(1)	Attainable retail price	ARP	52,500 EUR	Marketing Department
(2)	Dealer margins, taxes, import or export fees	-	26,250 EUR	Management Accounting Department
(3)	Net revenue	NR	26,250 EUR	(3) = (1) – (2)
(4)	Target return	TR	33.33%	Management Accounting Department
(5)	Target contribution margin	TCM	8,750 EUR	(5) = (3) * (4)
(6)	Allowable cost	AC	17,500 EUR	(6) = (3) – (5)

3.4.4 Creating the Segment-Specific Minimum Product (SSMP)

The SSMP will be technologically fully functional and fulfill the basic requirements of the segment within which the product is positioned. The starting point to define the SSMP is the predecessor product (Albers et al., 2015). As this version is typically outdated, its property profile usually is – compared to the contemporary competitor products – at the LIC level for almost all properties. If the property profile would be even below LIC level, the product is adjusted to meet all basic requirements of the segment within which the product is positioned.

The starting point for the cost base of the SSMP is the actual cost structure of its predecessor product. Next, the cost base is adjusted based on EoE and EoL to generate an actualized cost base for the new development project. EoE account for overall cost reduction effects due to maturing technologies and technical progress. EoL account for more specific cost reduction effects due to repetition and these are differentiated for individual components. Applying these effects to the cost base of the predecessor product provides an updated cost base for the new development project.

The cost base is further adjusted to account for cost benchmarks. A pool of cars belonging to the same segment provides cost benchmarks. For example, the cost benchmark for the engine may come from the predecessor, the cost benchmark for the axles from competitor A, and the cost benchmark for the external lighting system from competitor B. For a practically validated approach on how to estimate costs based on reference products, we refer to Hellweg (2026) and Hellweg et al. (2023). Finally, the benchmark-optimized cost base needs to be enriched to account for all upcoming mandatory technical regulatory and legal requirements.

3.4.5 Creating the Segment-Specific Enrichment Product (SSEP)

Next, constraints of commonality strategies are incorporated. Common parts, modular design, and product platforms are commonality strategies that are important for cost management (Ben

Mahmoud-Jouini and Lenfle, 2010; Ro et al., 2007; Thyssen et al., 2006). They enable reusing and sharing single components as well as entire product platforms across a set of diverging product derivates (Jiao et al., 2007; Pirmoradi et al., 2014). Development costs may be reduced as fewer components need to be developed, although the complexity of development increases (Davila and Wouters, 2004). Besides, greater production volumes can yield reduced production costs or lowered purchase prices (Skirde et al., 2016). Moreover, risk pooling effects may lead to lower inventory costs and better component availability (Wouters and Stadtherr, 2017).

Specifically, commonality strategies imply mandatory use of particular common parts, which likely increases the RPP as well as the product cost. The SSMP was characterized as product that typically possesses a PPP at the LIC level[4] because it was based on a predecessor product and includes parts that were chosen to benchmark-optimize costs. For the SSEP, some components are now exchanged for components that must be installed due to a commonality strategy. These will be likely newer and also be suitable for other, better products. However, the AC still serves as the upper bound for creating the SSEP, because the enrichment product must not exceed the overall allowable cost. Thus:

$$AC \geq \ DC_{SSEP} \geq \ DC_{SSMP}$$

$$RPP(SSEP) \geq RPP(SSMP)$$

3.4.6 Numerical Example Part II

The steps towards the SSMP and the SSEP are shown in Figure 22. Starting point is the cost base of the predecessor product of 21,000 EUR direct costs. The archival data of ECC suggest that continuous improvements lead to EoE across all major vehicle sections by 0.5% relative to the previous generation (see Table 12). Also, specific additional EoE cost reductions are expected for the major vehicle sections. ECC's data suggest that the EoL depend on the technical freedom and the degree of added value of individual parts, as shown in Table 13. Based on these parameters for EoL and EoE as well as using many detailed data on major vehicle sections and individual parts, a cost reduction of 900 EUR is estimated. Furthermore, due to fierce competition, benchmarks suggest that 4,850 EUR can be saved. Ensuring that the product conforms with the legal requirements causes additional direct cost bracket of 500 EUR. Thus, the SSMP has a cost of 15,750 EUR. Next, 310 EUR are added due to mandatory use of common parts, yielding a SSEP at a cost of 16,060 EUR.

[4] The PPP of the SSMP just fulfills the segment specific requirements. Hence, in most of the cases it is characterized by being at the lowest possible end of performance with a roundish profile on the LIC level. Theoretically though, the PPP of the SSMP could also have a more elaborated PPP, e.g. once the predecessor product still possesses an IBC or better performance equivalent.

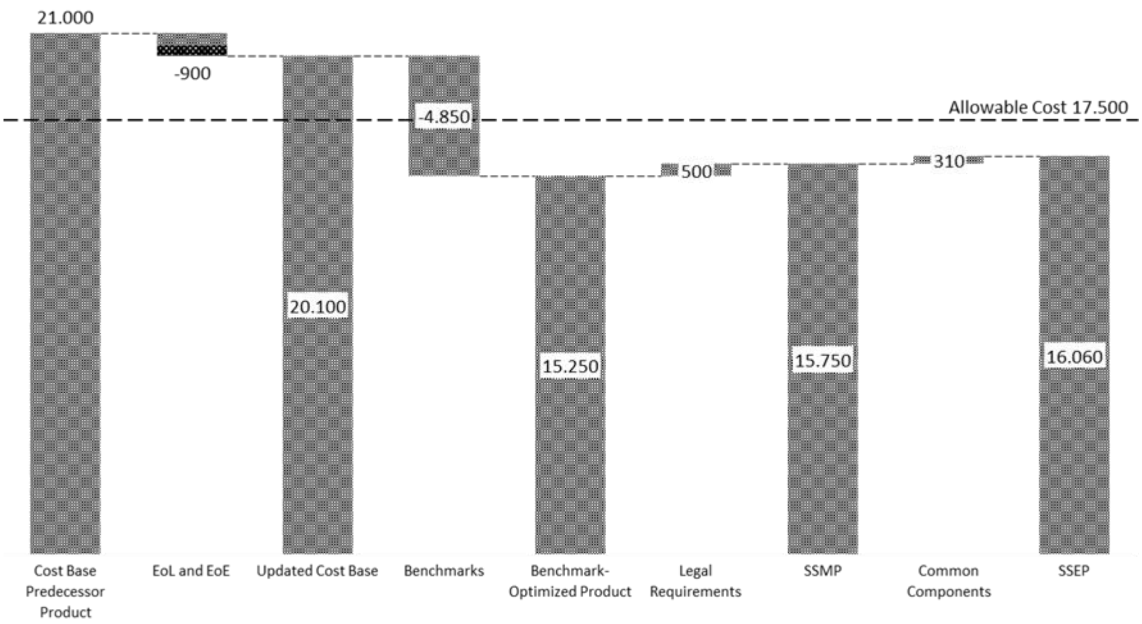

Figure 22 – The Steps towards the Target for the Direct Costs (DC) of the Segment-Specific Enrichment Product (SSEP) – Disguised Data

Table 12 - Economies of Efficiency (EoE) for Major Vehicle Sections – Disguised Data

Major Vehicle Section	Economies of Efficiency
General efficiency effects for the entire vehicle	0.5%
Chassis	2%
Interior	1%
Engine	1%
Battery	1.5%
Transmission	2%

Table 13 – Economies of Learning (EoL) per Individual Part – Disguised Data

		Degree of Technical Freedom		
		Low	Medium	High
Degree of Added Value	High	2%	3%	5%
	Medium	1%	2%	3%
	Low	0.5%	1.5%	2%

Please note that one enrichment activity may principally improve more than one property. For example, including a mandatory common part may simultaneously improve multiple properties. However, we decided to not include such cases in the numerical example of this chapter, because it would make the example unnecessarily complex. It would add columns to the model where the same enrichment activity is listed multiple times to indicate the specific property effects. For example, if larger brake discs would not only improve the driving dynamics of a car but also its suitability for everyday use (by requiring fewer changes), this particular technical product enrichment activity would be listed twice to account for its effects on property D as well as on property S. However, to keep the example concise, we did not include such case and rather focus on the individual enrichment logics presented in this contribution. Table 14 enumerates the required enrichment activities that are predefined due to the strategic choice of sharing certain components, which are partly overspecified in the example.

Table 14 – Numerical Example for the Selection of Enrichment Activities for Common Components – Disguised Data

								Property Points Needed to Reach Next Level or Target Level				
Row	**Technical Product Enrichment Possibility**	**Property**	**Additional Property Points (PP)**	**Additional Direct Costs**	**Cost-effectiveness**	**Remaining Budget**	**Enrichment Decision[a]**	**S[b]**	**D**	**C**	**Q**	**E**
1	Increase vehicle insulation	C	20	30 €	0.67	1,720.00 €	1	100	210	-19	161	61
2	Rear seat 40/60 folding	S	10	20 €	0.50	1,700.00 €	1	90	210	-19	161	61
3	Improve noise emissions	E	10	20 €	0.50	1,680.00 €	1	90	210	-19	161	51
4	Higher continuous charging performance	E	15	40 €	0.38	1,640.00 €	1	90	210	-19	161	36
5	Use sustainable materials	Q	30	100 €	0.30	1,540.00 €	1	90	210	-19	131	36
6	Improve braking performance – larger discs	D	10	50 €	0.20	1,490.00 €	1	90	200	-19	131	36
7	Increase battery size	E	10	50 €	0.20	1,440.00 €	1	90	200	-19	131	26

[a] Enrichment decisions: 1: Included in the SSEP. [b] Properties: Suitability for everyday use (S), driving dynamics (D), comfort (C), quality (Q), environmental compatibility & sustainability (E)

The resulting PPP of the SSMP equals – in our case – a circle where every key product property scores at the LIC level. As stated above, such shape of the SSMP is likely to be realized as usually, and as in our example, the predecessor baseline product is technology-wise outdated by the competitive basket. The use of common components leads in our case to a parallel shift of the reached property levels for the SSEP. Generally, the use of the predeveloped components could lead to any of the defined property levels: If the common component performs worse, a ULIC property level would theoretically be realized, but the minimum performance threshold advises against its usage; If the predeveloped product performs superior, a TOP or even BIC rating would be realized for the SSEP. Figure 23 shows the PPP of the SSMP and the SSEP.

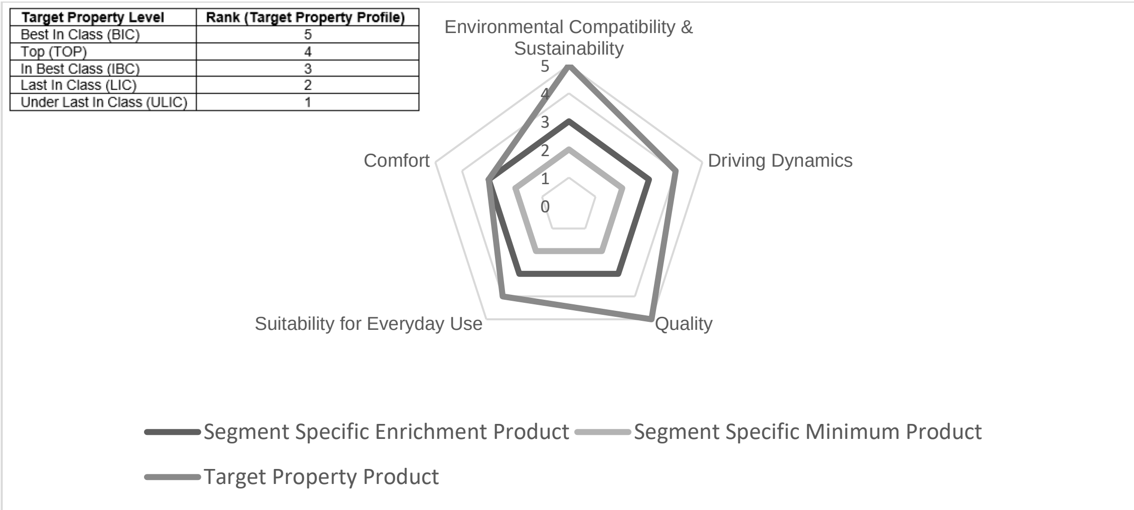

Figure 23 – Example Product Property Profile (PPP) of the Segment-Specific Minimum Product (SSMP) and the Segment-Specific Enrichment Product (SSEP) – Disguised Data

The SSMP and the SSEP reach the PP and property levels as outlined in Table 15.

Table 15 – Reached Property Levels and Reached Property Points (RPP) of the Segment-Specific Minimum Product (SSMP) and the Segment-Specific Enrichment Product (SSEP) – Disguised Data

Property	Property Level SSMP	Reached Property Points SSMP	Property Level SSEP	Reached Property Points SSEP
Suitability for everyday use (S)	LIC	90	IBC	100
Driving dynamics (D)	LIC	90	IBC	100
Comfort (C)	LIC	10	IBC	30
Quality (Q)	LIC	70	IBC	100
Environmental compatibility & sustainability (E)	LIC	85	IBC	120

3.4.7 Creating the Best of Budget Product (BoBP)

The third step configures a product by iteratively selecting cost-effective enrichment activities within the allowable cost budget. We present three approaches based on cost-effectiveness, which is the additional property points per additional direct cost associated with a potential technical product enrichment activity. Approach A improves across the entire set of properties, whereas Approach B first clusters the potential enrichment activities before using cost-effectiveness to determine the order of enrichment activities within the cluster. Approaches B1 and B2 differ in the way how they cluster the activities. All three approaches are function-wise a greedy algorithm that approximates a global optimum by repeated realization of local optima (García, 2025; Peng et al., 2018; Wu and Hao, 2015).

3.4.7.1 Approach A: Cost-effectiveness Maximization Across Unranked Properties

Cost-effectiveness here concerns the additional number of PP relative to the additional direct material costs. Accordingly, we define the objective function as follows, whereby the delta *d* indicates the realizable change in PP and DC relative to the product configuration without the technical product enrichment activity. The index *Pr* indicates that the delta in PP and DC needs to be calculated per individual property.

Target Function

$$Maximize\ Cost\ Effectiveness = Maximize\ \left(\frac{dPP_{Pr}}{dDC}\right)$$

Besides, three restrictions must be satisfied. First, the TARGET restriction is only satisfied if the current property level is below the target property level. If a product property is already on the target level (or even better), this restriction is not satisfied, because further improvement is pointless. The resources are better spent on the remaining properties, whose individual target level has not yet been reached. Whilst this forced shift to remaining properties is in most cases reasonable, it could lead to a scenario in which financial resources remain unused as our numerical example will illustrate.

subject to

$$TARGET = \begin{Bmatrix} 1, if\ PP_{TargetRank} > PP_{Rank\ i} \\ 0, else \end{Bmatrix} = 1$$

Second, the STEP restriction requires that the sum of increased PP from all chosen enrichment activities, i.e. the whole set, needs to be sufficient to reach the next property level, for example improving from LIC to IBC. Hence, the sum of gained PP concerning a certain target property (Pr) over all possible enrichment activities A must be at least equal to the required PPI concerning this target property.

$$STEP = \begin{Bmatrix} 1, if\ \sum_{a=1}^{A} dRPP_{Pr} \geq PPI_{Pr} \\ 0, else \end{Bmatrix} = 1$$

Third, the COST restriction demands that the sum of all realized additional enrichment activities must not exceed the AC of the product. Accordingly, the direct costs of the SSEP are only allowed to be increased up to the level of the overall allowable direct costs.

$$COST = \begin{Bmatrix} 1, if\ \sum_{a=1}^{A} DC_{SSEP} \leq AC \\ 0, else \end{Bmatrix} = 1$$

3.4.7.2 Approach B1: Properties Ranked by the Target Property Level

Approach B1 and Approach B2 first cluster the technical product enrichment activities based on the importance of properties for improving the product (I_{Pr}). Next, they use cost-effectiveness to determine the order of enrichment activities within the cluster. The two approaches differ in the way how they determine I_{Pr}.

In Approach B1, firstly, the target property level determines the importance of a property. For example, if the product is supposed to reach a BIC level concerning Property A and only an IBC level concerning Property B, then Property A is more important than Property B.

$$Rank_{Startegy,Pr} = f(Target\ Property\ Profile) = \begin{Bmatrix} 5, if\ BIC \\ 4, if\ TOP \\ 3, if\ IBC \\ 2, if\ LIC \\ 1, if\ ULIC \end{Bmatrix}$$

Secondly, the importance of a property is ranked based on market research, for example using conjoint analysis.

$$Rank_{Marketing,Pr} = f(Conjoint\ Analysis_{Pr})$$

Multiplying both ranks provides the I_{Pr}[5].

$$I_{Pr} = Rank_{Strategy,Pr} * Rank_{Marketing,Pr}$$

All properties are ranked according to their I_{Pr} and then we order the enrichment activities grouped by the properties they are primarily addressing. Accordingly, $\overline{\mathrm{A}_{Pr,A}}$ is a subset of all enrichment activities primarily concerning Property A.

$$\forall\ \overline{\mathrm{A}_{Pr}} \subseteq A$$

Within each group of technical product enrichment activities, these are ordered based on their cost-effectiveness.

We divide the master problem into smaller sub-problems that collectively solve it. Accordingly, we define the property points gap (PPG) as the difference between the required target level of PP and the actually reached level of PP concerning a certain property, summed for all product properties. In other words, how many PP are still lacking. The procedure can be understood as iteratively addressing a sequence of subproblems – selecting cost-effective enrichments within each prioritized property – that jointly aim to reduce the overall property points gap (PPG). The overall guiding objective – the minimization of the gap between the required and the reached PP – is pursued indirectly through this sequence of local choices.

Target Function

$$Minimize\ PPG = Minimize\ (required\ PP_{Target\ Product} - RPP_{SSEP})$$

subject to

[5] Please note that if the two perspectives would not use the same scale, e.g. having only three strategic rank levels and five concerning the marketing dimension, one would need to normalize the scales first to avoid implicitly assigning a higher importance to the dimension that has a more diversified scale.

$$PPG = \sum_{Pr=1}^{PR} PPG_{Pr}$$

As for Approach A, the three constraints of TARGET, STEP, and COST apply. Additionally, a technical product enrichment activity needs to have a minimum level of cost-effectiveness. This MIN restriction is important to prevent that within a subset of all enrichment activities primarily concerning a particular highly important property, technical product enrichment activities keep being selected even if they have an inferior level of cost-effectiveness. It would be better to stop and move on to the next important property and its enrichment activities. A pure cluster cost-effectiveness logic is likely to be inefficient as in such cases any enrichment activity concerning a higher valued property is prioritized compared to any activity that improves a lower valued property. At some point, the remaining budget for direct cost is better spent on highly cost-effective enrichment activities for another property that is less important. Accordingly, we define a lower bound of cost-effectiveness that an enrichment activity needs to realize in order to be considered as an improved state of the product.

$$MIN = \begin{Bmatrix} 1, if \ \dfrac{dRPP_{Pr}}{dDC} \geq 0.01 \\ 0, else \end{Bmatrix} = 1$$

3.4.7.3 Approach B2: Properties Ranked by the Deviation from the Target Property Level

Approach B2 works as B1 but the I_{Pr} is determined in a different way. A first criterion is the deviation between the target property level and the PPP of the SSEP. For example, if the target property level is BIC and the property level of the SSEP is IBC, then there is a deviation of two property levels. The bigger the deviation between the target property level and the reached property level of the SSEP, the higher its priority for enrichment.

$$Enrichment\ Group_{Pr} = Property\ Level_{Target\ Product_{Pr}} - Property\ Level_{SSEP_{Pr}}$$

For properties that have the same deviation in terms of property levels, the PPG_{Pr} serves as secondary criterion. Specifically, we compare the target number of PP to the currently reached sum of points. For both criteria, a higher number, meaning a larger gap between the property level respectively the PP, indicates a higher importance.

$$I_{Pr} = f(Enrichment\ Group_{Pr}, PPG_{Pr})$$

3.4.8 Numerical Example Part III

3.4.8.1 Approach A

The first seven rows of Table 16 show the technical product enrichment activities that have already been selected in the SSEP due to the mandatory use of common parts, some of which may be overspecified for the current product.

The selection of technical product enrichment activities towards the BoBP starts on row eight. These are sorted based on cost-effectiveness (the additional PP ÷ additional direct cost) in descending order. All enrichment activities are selected as long as the TARGET, STEP, and COST restrictions are satisfied.

Rows 8, 11 and 17 illustrate that enrichment activities for property Q are selected, because all constraints are satisfied. Row 21 for property Q is not selected anymore because the target property level has already been reached (TARGET constraint).

Rows 9, 13 and 19 illustrate that enrichment activities for property S are selected, because all constraints are satisfied. Rows 22 and 25 are not selected anymore, because the target property level has already been reached (TARGET constraint). This outcome is suboptimal with respect to the underlying combinatorial problem as row 22 could have been afforded within the remaining budget and would have lifted property S to the BIC level. The example demonstrates that the proposed method, being a greedy heuristic, can produce solutions that are dominated by alternative feasible configurations. In practical use, such cases can be identified by inspection and corrected on a case-by-case basis.

Rows 10, 15, 16, and 20 provide examples of the COST constraint. For property D, the next higher property rating TOP requires 200 PP and this could be reached with these enrichment activities that bring 65 + 48 + 45 + 45 = 203 PP at a total additional direct cost of 980 EUR. At the point where the first of these activities appears in the cost-effectiveness ranking (row 10), the remaining budget is 1,400 EUR, which would nominally suffice. However, reaching the next property level for D requires all four activities to be realized jointly (STEP constraint). Since the cost-effectiveness-based selection processes all properties simultaneously, enrichment activities for other properties – specifically for Q (rows 8, 11, 17), S (rows 9, 13, 19), and E (row 12) – are ranked in between and consume 710 EUR of the budget before the last D activity (row 20) is reached. At that point, only 730 EUR remain, which is insufficient to cover the combined 980 EUR. Hence, no individual D activity is selected, because selecting any subset would not satisfy the STEP constraint: the gained PP would remain below the threshold for the next property level and thus would not result in a perceptible product improvement.

Rows 14 and 18 illustrate that enrichment activities for property E are not selected, because the target level is already reached after selecting the enrichment activity on row 12 (TARGET constraint).

Rows 23, 24, and 26–29 present the available enrichment activities to improve product property C, which are not selected. The TARGET constraint is not satisfied, as the target property level of IBC is already reached by the SSEP.

In this example, all target property levels are reached, except for driving dynamics (D). The financial budget is not fully exploited and 730 EUR is left, at least at this moment in the product development process. With this budget, a significant improvement over the SSEP to reach a higher property level for driving dynamics could not be reached.

Table 16 – Numerical Example for the Selection of Enrichment Activities following Approach A – Disguised Data

								Property Points (PP) Needed to Reach Next Level or Target Property Level.				
Row	Technical Product Enrichment Possibility	Property	Additional Property Points	Additional Direct Cost	Cost-effectiveness	Remaining Budget	Enrichment Decision[a]	S[b]	D	C	Q	E
1	Increase vehicle insulation	C	20	30 €	0.67	1,720 €	1	100	210	-19	161	61
2	Rear seat 40/60 folding	S	10	20 €	0.50	1,700 €	1	90	210	-19	161	61
3	Improve noise emissions	E	10	20 €	0.50	1,680 €	1	90	210	-19	161	51
4	Higher continuous charging performance	E	15	40 €	0.38	1,640 €	1	90	210	-19	161	36
5	Use sustainable materials	Q	30	100 €	0.30	1,540 €	1	90	210	-19	131	36
6	Improve braking performance - larger discs	D	10	50 €	0.20	1,490 €	1	90	200	-19	131	36
7	Increase battery size	E	10	50 €	0.20	1,440 €	1	90	200	-19	131	26
8	Add rear light strip	Q	65	20 €	3.25	1,420 €	2	90	200	-19	66	26
9	Add roof rails with sensor	S	40	20 €	2.00	1,400 €	2	50	200	-19	66	26
10	Increase top speed [180 km/h]	D	65	200 €	0.33	1,400 €	5	50	200	-19	66	26
11	Improve display	Q	45	140 €	0.32	1,260 €	2	50	200	-19	21	26
12	Efficiency - CW-A	E	30	100 €	0.30	1,160 €	2	50	200	-19	21	-4
13	Increased trailer load	S	30	110 €	0.27	1,050 €	2	20	200	-19	21	-4
14	Higher maximum charging power	E	50	200 €	0.25	1,050 €	3	20	200	-19	21	-4
15	Increase acceleration 0-100 [6 seconds]	D	48	200 €	0.24	1,050 €	5	20	200	-19	21	-4
16	Increase performance robustness - different thermal management R844 instead of R1234	D	45	200 €	0.23	1,050 €	5	20	200	-19	21	-4
17	Use recycled materials	Q	35	200 €	0.18	850 €	2	20	200	-19	-14	-4
18	Efficiency - rolling resistance	E	40	230 €	0.17	850 €	3	20	200	-19	-14	-4
19	Rear seat 40/20/40 folding	S	20	120 €	0.17	730 €	2	0	200	-19	-14	-4
20	Permanent four-wheel drive	D	45	380 €	0.12	730 €	5	0	200	-19	-14	-4
21	Optimize exterior design (bumper)	Q	35	300 €	0.12	730 €	3	0	200	-19	-14	-4
22	Add simple roof rails (painted)	S	20	180 €	0.11	730 €	3	0	200	-19	-14	-4
23	Software – Improve focus FAS / LEVEL	C	20	240 €	0.08	730 €	3	0	200	-19	-14	-4
24	Add ambient lighting	C	10	120 €	0.08	730 €	3	0	200	-19	-14	-4
25	Add frunk	S	10	180 €	0.06	730 €	3	0	200	-19	-14	-4
26	Improve vibration comfort	C	10	220 €	0.05	730 €	3	0	200	-19	-14	-4
27	Software – Focus on improving connectivity	C	10	300 €	0.03	730 €	3	0	200	-19	-14	-4
28	Add leather in the interior	C	10	300 €	0.03	730 €	3	0	200	-19	-14	-4
29	Improve interior quality	C	10	600 €	0.02	730 €	3	0	200	-19	-14	-4
	Reached Property Points (RPP)							190	100	30	245	150
	Reached Property Level (Target Achieved?)							TOP (Yes)	IBC (No)	IBC (Yes)	BIC (Yes)	BIC (Yes)

[a] Enrichment decisions: 1: Included in the SSEP. 2: Included in the BoBP. 3: Not included because property target level has already been reached (TARGET constraint). 4: Not included because next property level cannot be reached with the remaining technical product enrichment possibilities (STEP constraint). 5: Not included because next property target cannot be reached with the remaining budget (COST constraint). In case multiple constraints are violated, only one is listed here as the heuristic advises against the enrichment activity anyways. [b] Properties: Suitability for everyday use (S), driving dynamics (D), comfort (C), quality (Q), environmental compatibility & sustainability (E)

Property-wise, we expect a homogeneously improved PPP across all properties reaching an average IBC property ranking as the underlying improvement is purely sorted by cost-effectiveness without any implied preference order. Hence, in a theoretical example where all potential product improvements are equally distributed, it would lead to roundish improvement over all properties in equal dimensions. However, as our example inspired by a realistic case illustrates in Figure 24, the BoBP created by Approach A possesses a well pronounced PPP that almost matches the target PPP.

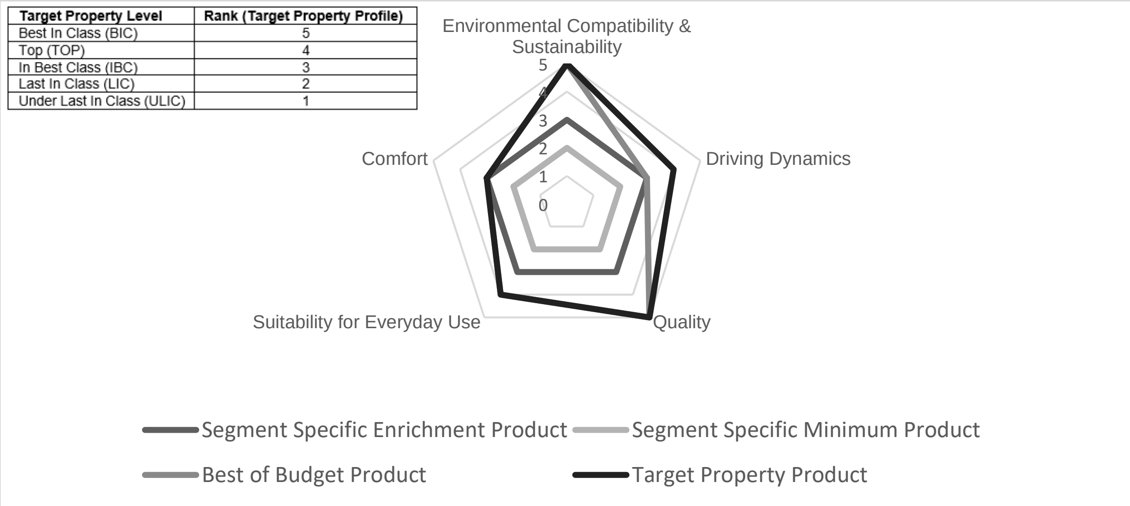

Figure 24 – Example Product Property Profile (PPP) after Realizing Maximization Approach A – Disguised Data

3.4.8.2 Approach B1

The potential technical product enrichment activities are first ranked according to the importance of the properties (Q, D, C, S, and E) and second based on their cost-effectiveness. The improvement logic of Approach B1 follows an iterative loop of minimizing the PPG per property. The order of the properties is shown in Table 17.

Table 17 – Ranking Property Importance with Approach B1 – Disguised Data

Property	Target Property Level	Customer Preference Order	Importance of the Property I_{Pr}	Rank for Enrichment Activities
Suitability for everyday use (S)	4 (TOP)	2	(4)*(2) = 8	4 (Fourth)
Driving dynamics (D)	4 (TOP)	4	(4)*(4) = 16	2 (Second)
Comfort (C)	3 (IBC)	3	(3)*(3) = 9	3 (Third)
Quality (Q)	5 (BIC)	5	(5)*(5) = 25	1(First)
Environmental compatibility & sustainability (E)	5 (BIC)	1	(5)*(1) = 5	5 (Last)

In Table 18, we present activities to improve the most important property Q. Enrichment activities are selected until the target property level is reached. Row 11 is an example that the TARGET constraint is not satisfied, because the previously selected enrichment activities are already sufficient to reach the target property level BIC for property Q.

Rows 12–15 present activities to improve the second most important product property D until the target level is reached.

Next, rows 16–21 present activities to improve the third most important product property C. Since the targeted level of property C is already reached by the SSEP, the TARGET constraint impedes any further enrichment activities.

On rows 22−26, no enrichment activities for property S are selected because the required amount of PP to reach the next property level is not covered by the remaining financial resources. The enrichment of the option listed in row 22 would be financially possible, but this is not selected because his would not be sufficient to reach the next property level (STEP constraint). To reach the next property level of TOP, the next three enrichment activities on rows 22–24 would need to be realized. However, these would add supplementary costs of 250 EUR whilst the remaining open budget allows only for coverage of 100 EUR. Hence, the COST constraint blocks further enrichment of property S given the costly options available.

Rows 27−29 show the enrichment activities for property E. The activity on row 27 is selected as this just fits the remaining budget of 100 EUR and suffices to reach the next property level, which is also the target property level. Hence, the remaining activities are not selected as the TARGET constraint applies.

In this example, the result is that the target property level is not achieved in the BoBP for property S, which is in line with the importance of this property. The approach placed special emphasis on improving the most important properties Q and D.

Table 18 – Numerical Example for the Selection of Enrichment Activities following Approach B1 – Disguised Data

								Property Points Needed to Reach Next Level or Target Property Level.				
Row	**Technical Product Enrichment Possibility**	**Property**	**Additional Property Points**	**Additional Direct Costs**	**Cost Effectiveness**	**Remaining Budget**	**Enrichment Decision[a]**	**S[b]**	**D**	**C**	**Q**	**E**
1	Use sustainable materials	Q	30	100 €	0.30	1,650 €	1	100	210	1	131	61
2	Improve braking performance - larger discs	D	10	50 €	0.20	1,600 €	1	100	200	1	131	61
3	Increase vehicle insulation	C	20	30 €	0.67	1,570 €	1	100	200	-19	131	61
4	Rear seat 40/60 folding	S	10	20 €	0.50	1,550 €	1	90	200	-19	131	61
5	Improve noise emissions	E	10	20 €	0.50	1,530 €	1	90	200	-19	131	51
6	Higher continuous charging performance	E	15	40 €	0.38	1,490 €	1	90	200	-19	131	36
7	Increase battery size	E	10	50 €	0.20	1,440 €	1	90	200	-19	131	26
8	Add rear light strip	Q	65	20 €	3.25	1,420 €	2	90	200	-19	66	26
9	Improve display	Q	45	140 €	0.32	1,280 €	2	90	200	-19	21	26
10	Use recycled materials	Q	35	200 €	0.18	1,080 €	2	90	200	-19	-14	26
11	Optimize exterior design (bumper)	Q	35	300 €	0.12	1,080 €	3	90	200	-19	-14	26
12	Increase top speed [180 km/h]	D	65	200 €	0.33	880 €	2	90	135	-19	-14	26
13	Increase acceleration 0-100 [6 seconds]	D	48	200 €	0.24	680 €	2	90	87	-19	-14	26
14	Increase performance robustness - different thermal management R844 instead of R1234	D	45	200 €	0.23	480 €	2	90	42	-19	-14	26
15	Permanent four-wheel drive	D	45	380 €	0.12	100 €	2	90	-3	-19	-14	26
16	Software – Improve focus FAS / LEVEL	C	20	240 €	0.08	100 €	3	90	-3	-19	-14	26
17	Add ambient lighting	C	10	120 €	0.08	100 €	3	90	-3	-19	-14	26
18	Improve vibration comfort	C	10	220 €	0.05	100 €	3	90	-3	-19	-14	26
19	Software – Focus on improving connectivity	C	10	300 €	0.03	100 €	3	90	-3	-19	-14	26
20	Add leather in the interior	C	10	300 €	0.03	100 €	3	90	-3	-19	-14	26
21	Improve interior quality	C	10	600 €	0.02	100 €	3	90	-3	-19	-14	26
22	Add roof rails with sensor	S	40	20 €	2.00	100 €	5	90	-3	-19	-14	26
23	Increased trailer load	S	30	110 €	0.27	100 €	5	90	-3	-19	-14	26
24	Rear seat 40/20/40 folding	S	20	120 €	0.17	100 €	5	90	-3	-19	-14	26
25	Add simple roof rails (painted)	S	20	180 €	0.11	100 €	5	90	-3	-19	-14	26
26	Add frunk	S	10	180 €	0.06	100 €	5	90	-3	-19	-14	26
27	Efficiency - CW-A	E	30	100 €	0.30	0 €	2	90	-3	-19	-14	26
28	Higher maximum charging power	E	50	200 €	0.25	0 €	3	90	-3	-19	-14	-4
29	Efficiency - rolling resistance	E	40	230 €	0.17	0 €	3	90	-3	-19	-14	-4
	Reached Property Points (RPP)							100	303	30	245	150
	Reached Property Level (Target Achieved?)							IBC (No)	BIC (Yes)	IBC (Yes)	BIC (Yes)	BIC (Yes)

[a] Enrichment decisions: 1: Included in the SSEP. 2: Included in the BoBP. 3: Not included because property target level has already been reached (TARGET constraint). 4: Not included because next property level cannot be reached with the remaining technical product enrichment possibilities (STEP constraint). 5: Not included because next property target cannot be reached with the remaining budget (COST constraint). In case multiple constraints are violated, only one is listed here as the heuristic advises against the enrichment activity anyways. [b] Properties: Suitability for everyday use (S), driving dynamics (D), comfort (C), quality (Q), environmental compatibility & sustainability (E)

Property-wise, we expect a heterogeneously improved PPP across all properties reaching a diverse set of property levels as the individual properties are treated with a distinct level of importance. In Figure 25, we can see a clearly positioned PPP of the BoBP placing special emphasis on the properties Q, D, and E while keeping all remaining properties at the level of the SSEP.

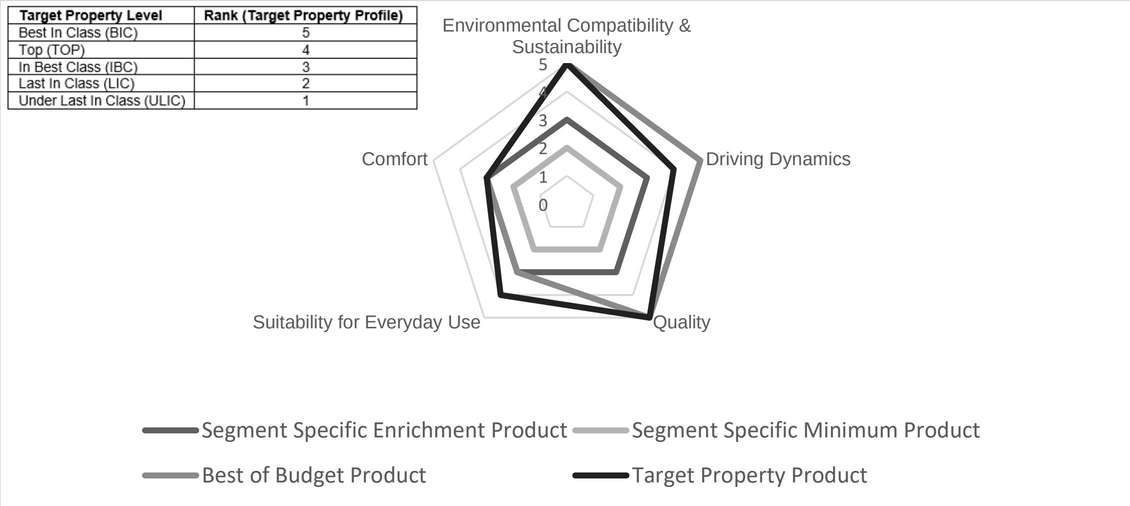

Figure 25 – Example Product Property Profile (PPP) after Realizing Maximization Approach B1 – Disguised Data

3.4.8.3 Approach B2

This time, the importance of the properties is determined based on the gap between the reached property level in the SSEP and the target property level. If this gap is equal for several properties, then the gap in terms of PP becomes the second criterion. The ranking order is shown in Table 19 which is this time Q, E, D, S, and C. The results of the realized enrichment activities are shown in Table 20.

Table 19 – Ranking Property Importance with Approach B2 – Disguised Data

Property	SSEP Property Level/Points (PP)	Target Property Level/Points (PP)	Gap in Property Level/Points (PP)	Ranking Order for Enrichment Activities
Suitability for every-day use (S)	IBC/100	TOP/190	1/90	4 (Fourth)
Driving dynamics (D)	IBC/100	TOP/300	1/200	3 (Third)
Comfort (C)	IBC/30	IBC/11	0/0	5 (Last)
Quality (Q)	IBC/100	BIC/231	2/131	1(First)
Environmental compatibility & sustainability (E)	IBC/120	BIC/146	2/26	2 (Second)

Table 20 – Numerical Example for the Selection of Enrichment Activities following Approach B2 – Disguised Data

								Property Points Needed to Reach Next Level or Target Level				
Row	**Technical Product Enrichment Possibility**	**Property**	**Additional Property Points**	**Additional Direct Costs**	**Cost Effectiveness**	**Remaining Budget**	**Enrichment Decision[a]**	**S[b]**	**D**	**C**	**Q**	**E**
1	Use sustainable materials	Q	30	100 €	0.30	1,650 €	1	100	210	1	131	61
2	Improve noise emissions	E	10	20 €	0.50	1,630 €	1	100	210	1	131	51
3	Higher continuous charging performance	E	15	40 €	0.38	1,590 €	1	100	210	1	131	36
4	Increase battery size	E	10	50 €	0.20	1,540 €	1	100	210	1	131	26
5	Improve braking performance - larger discs	D	10	50 €	0.20	1,490 €	1	100	200	1	131	26
6	Rear seat 40/60 folding	S	10	20 €	0.50	1,470 €	1	90	200	1	131	26
7	Increase vehicle insulation	C	20	30 €	0.67	1,440 €	1	90	200	-19	131	26
8	Add rear light strip	Q	65	20 €	3.25	1,420 €	2	90	200	-19	66	26
9	Improve display	Q	45	140 €	0.32	1,280 €	2	90	200	-19	21	26
10	Use recycled materials	Q	35	200 €	0.18	1,080 €	2	90	200	-19	-14	26
11	Optimize exterior design (bumper)	Q	35	300 €	0.12	1,080 €	3	90	200	-19	-14	26
12	Efficiency - CW-A	E	30	100 €	0.30	980 €	2	90	200	-19	-14	-4
13	Higher maximum charging power	E	50	200 €	0.25	980 €	3	90	200	-19	-14	-4
14	Efficiency - rolling resistance	E	40	230 €	0.17	980 €	3	90	200	-19	-14	-4
15	Increase top speed [180 km/h]	D	65	200 €	0.33	780 €	2	90	135	-19	-14	-4
16	Increase acceleration 0-100 [6 seconds]	D	48	200 €	0.24	580 €	2	90	87	-19	-14	-4
17	Increase performance robustness - different thermal management R844 instead of R1234	D	45	200 €	0.23	380 €	2	90	42	-19	-14	-4
18	Permanent four-wheel drive	D	45	380 €	0.12	- €	2	90	-3	-19	-14	-4
19	Add roof rails with sensor	S	40	20 €	2.00	- €	5	90	-3	-19	-14	-4
20	Increased trailer load	S	30	110 €	0.27	- €	5	90	-3	-19	-14	-4
21	Rear seat 40/20/40 folding	S	20	120 €	0.17	- €	5	90	-3	-19	-14	-4
22	Add simple roof rails (painted)	S	20	180 €	0.11	- €	5	90	-3	-19	-14	-4
23	Add frunk	S	10	180 €	0.06	- €	5	90	-3	-19	-14	-4
24	Software – Improve focus FAS / LEVEL	C	20	240 €	0.08	- €	3	90	-3	-19	-14	-4
25	Add ambient lighting	C	10	120 €	0.08	- €	3	90	-3	-19	-14	-4
26	Improve vibration comfort	C	10	220 €	0.05	- €	3	90	-3	-19	-14	-4
27	Software – Focus on improving connectivity	C	10	300 €	0.03	- €	3	90	-3	-19	-14	-4
28	Add leather in the interior	C	10	300 €	0.03	- €	3	90	-3	-19	-14	-4
29	Improve interior quality	C	10	600 €	0.02	- €	3	90	-3	-19	-14	-4
	Reached Property Points (RPP)							100	303	30	245	150
	Reached Property Level (Target Achieved?)							IBC (No)	BIC (Yes)	IBC (Yes)	BIC (Yes)	BIC (Yes)

[a] Enrichment decisions: 1: Included in the SSEP. 2: Included in the BoBP. 3: Not included because property target level has already been reached (TARGET constraint). 4: Not included because next property level cannot be reached with the remaining technical product enrichment possibilities (STEP constraint). 5: Not included because next property target cannot be reached with the remaining budget (COST constraint). In case multiple constraints are violated, only one is listed here as the heuristic advises against the enrichment activity anyways. [b] Properties: Suitability for everyday use (S), driving dynamics (D), comfort (C), quality (Q), environmental compatibility & sustainability (E)

Property-wise, we again expect a heterogeneously improved PPP that possesses a clear prioritization among its core properties. Figure 26 illustrates the PPP of the BoBP. Similarly, to Approach B1, the PPP is clearly characterized and positioned as it places special emphasis on the properties D, Q, and E.

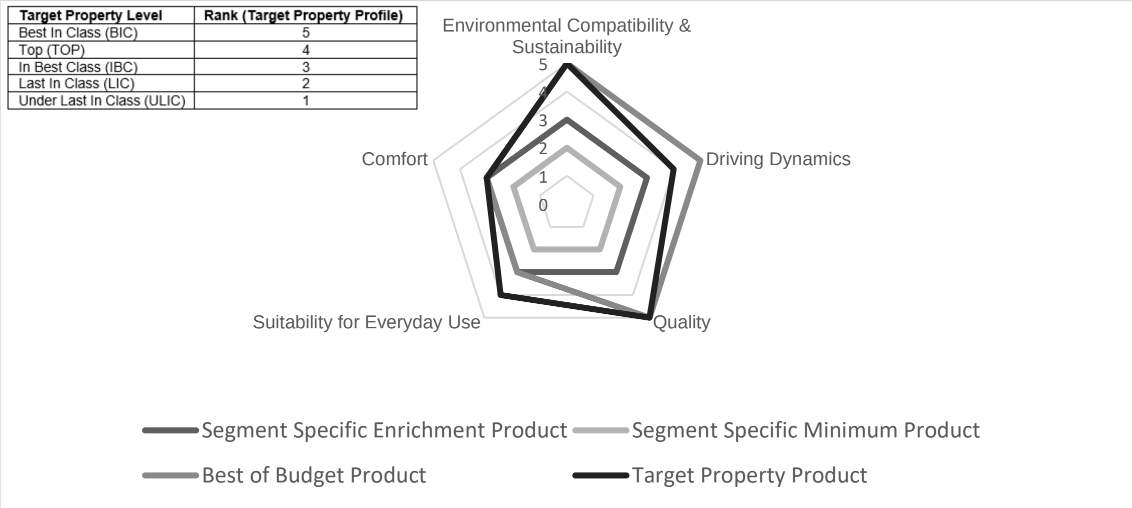

Figure 26 – Example Product Property Profile (PPP) after Realizing Maximization Approach B2 – Disguised Data

3.5 Discussion and Conclusion

We presented an extension of target costing that can be used during the development of complex, interdependent products under significant cost pressure. The central idea is to create a minimum product that reflects cost benchmarks and learning effects, then to incorporate common parts for managing costs across a product group, and finally to use cost-effectiveness to maximally improve product properties within a given cost budget. The study was inspired by practice and conducted as action research following the ideas of Checkland and Holwell (1998).

As examined in section 3.2.3, the target costing and value engineering literature assumes that the cost gap between allowable and drifting cost can generally be closed by cost management activities such as supplier development, changes in material, specifications or design, and cost tradeoffs (Ellram, 2002). Few studies address how the cost gap can be closed (Ibusuki and Kaminski, 2007; Iranmanesh and Thomson, 2008) or the situation when the cost gap cannot be closed by using such approaches (Thore Olsson et al., 2018). The question becomes how to identify a strong realizable product within the given financial boundaries and design restrictions. Furthermore, it can be realistic to consider the relevance of product property improvements as a step function of notable improvements from the customer's perspective in comparison to competitor products.

The contribution of this study is to formulate the product enrichment decision under cost pressure as a constrained combinatorial optimization problem and to propose a greedy heuristic that addresses it. The approach offers transparency, modest data requirements, and practical applicability, which are decisive advantages in the industrial settings that motivated the study. In order to account for cost benchmarks and restrictions in design freedom – mandatory common parts in particular – the SSEP is created. This serves as a baseline for all enrichment activities, in order to create the BoBP: the configuration recommended by the proposed greedy heuristic within the given allowable cost. This study presented two approaches to derive this BoBP, always based on cost-effectiveness. Approach A selects the most cost-effective product improvements across all product properties. Approach B first prioritizes product properties and then selects the most cost-effective product improvements separately for each product property. Two different methods for prioritizing product properties were suggested.

Property-wise, the approaches create distinguishable PPPs. Applying Approach A improves the PPP solely on the underlying logic of cost-effectiveness. If all properties and the cost-effectiveness of their respective enrichment activities would be heterogeneously distributed, Approach A would lead to a roundish PPP that maximally exploits the realizable PP without emphasizing certain product properties. Given the resulting PPP of Approach A was roundish, the product is likely to be perceived to be characteristically undefined as there is no room to induce a certain brand identity into the product. In our setup, however, the available enrichment activities were not equally distributed concerning their cost-effectiveness across the individual properties. Hence, the resulting PPP is pronounced and matches all but one target level. In other words, the resulting PPP matches the target PPP at the expense of property D. Approach B1 and Approach B2 on the other hand use a clear prioritization of the underlying properties based on distinguishable approaches to define the importance of a certain property. Hence, they place more emphasis on prioritizing certain product properties to create a characteristic product and do not face the issue of potentially creating an undistinguishable roundish PPP. Accordingly, the product profile after applying these approaches is not roundish but edgy with a clear focus spot. Especially Approach B1 allows for combining a strategic and marketing perspective to shape the product's profile to match the overarching corporate identity. Approach B2 on the other hand serves to minimize deviations between an aspired and a reached property level in the development process. In both approaches, a key to success is to satisfy the customer expectations by the employed rank order[1]. Table 21 provides a summary of the property effects of the presented maximization approaches.

Table 21 – Summary of the Property Effects of the Presented Maximization Approaches

	Approach A	Approach B1	Approach B2
Property Preference	No Property Preference	Preference according to individually defined importance	
Property Profile	Edgy (random distribution of enrichment activities and their cost-effectiveness), otherwise roundish with lack of character.	Edgy and characteristically pronounced.	
Main Purpose	Broadly enhance the capability of the product whilst requiring the least input information.	Strategically shape the product	Reduce deviations between desired and realized product capability

As always, there are also limitations to this study. The first limitation is that we could not provide empirical results of a full-scale implementation. Nevertheless, the close collaboration with cost

[1] In the numerical example of Chapter 3.4.8, Approach B1 and B2 ultimately led to the same PPP. Whilst this is theoretically possible – as in the given example – this is not necessarily the case as both prioritization logics lead to a different preference order. In the given example, suppose the last realized technical enrichment activity of "Efficiency - CW-A" of Approach B1 would be only one Euro more expensive, it would not be installed leading to a different PPP than Approach B2.

experts in product development at ECC provided many inputs for developing a pragmatic approach and their responses to the prototype applications support the relevance of this approach.

A second limitation is that the overall, more general logic of the approach was implemented with several choices that were specific to the company ECC, and these may be different in other contexts. The overall, general logic of the approach is to first configure a product based on specific initial considerations and then to use cost-effectiveness to select further technical product enrichment activities within the remaining allowable direct cost budget. At ECC, these initial considerations were cost benchmarks, legal requirements, economies of learning and efficiency, and common parts. Some of these choices may be different in another company. Also, the approach as described in this study includes specific considerations of ECC for determining the importance of product properties. These may also be different in another organization.

Based on this study, several suggestions for future research can be made. First, the approach developed together with the case company ECC could be applied and tested in other manufacturing companies. Such studies could experiment with the approach that has the same overall logic but different specific initial considerations or different ways to prioritize product properties. Similarly, studies in other industries or in medium-sized companies may provide worthwhile variations of the approach. Cost pressure is not unique to ECC but specific initial considerations may vary, as well as the specific elements, such as a step function for the importance of product property improvements, or the prioritization of product properties.

More broadly, future research could address product development situations in which strong cost pressure necessitates difficult tradeoffs between product properties given hard cost constraints (Thore Olsson et al., 2018). The research would aim to better understand how tradeoffs are being made, and which methods are suitable under realistic conditions regarding data availability and unpredictability of customer preferences, competitor actions, and technological developments.

4 Contribution Margin Forecast Accuracy in New Product Development: A Proprietary Archival Study

Abstract

Accurate contribution margin forecasts are a critical success factor for companies deciding which projects to approve and where to invest. Yet, despite this importance to have accurate forecasts, knowledge on what drives *Forecast Accuracy* is scarce. To contribute to this gap, we benefit from a unique opportunity to investigate three potentially influencing factors – *Time Effects, Production Effects, Segment Importance* – on *Forecast Accuracy* based on archival data of an automotive original equipment manufacturer. Whilst *Time Effects* are found to have no significant influence, *Production Effects* significantly affect *Forecast Accuracy* with inhouse-produced products being more accurately forecasted. The relationship between *Segment Importance* and *Forecast Accuracy* is partly significant, with the lowest-volume segment exhibiting significantly less accurate forecasts. Management wise, these insights urge for caution to establish tight information exchange with external suppliers and to not neglect complex niche product segments during new product development to precisely forecast their cost base and make informed financial tradeoff decisions.

Keywords: Forecast Accuracy; Forecast Error; Cost Overruns; New Product Development; Financial Tradeoffs

4.1 Introduction

For manufacturers, estimating the contribution margin per product is a critical activity – especially during the early stages of new product development (NPD) – where between 70 to 80 percent of a product's costs are determined (Rush and Roy, 2000). The earlier cost gaps between the allowable and the expected costs become visible, the more effectively cost management can close them (Ax et al., 2008; Ellram, 2002). Cost forecasting links engineering and cost management, guiding design decisions choices and investment decisions: overestimating costs can lead to the premature rejection of potentially profitable products; underestimating costs can increase the risk of financial loss during production (Hammann, 2024). Consequently, cost estimation has been extensively studied across civil engineering (Flyvbjerg et al., 2003, 2002), project management (Frimpong et al., 2003), engineering management (Qian and Ben-Arieh, 2008), management accounting (Jordan and Messner, 2020), and operations management (Fildes et al., 2008).

Yet – despite its importance – the empirical literature on cost-related forecast accuracy suffers from a persistent limitation, namely data scarcity. The resulting deficiency of data availability remains an issue as companies are not required to disclose these sensitive information (Disch, 2024). Researchers therefore rely on surveys, experiments, simulations or proxy approaches that combine disclosed financial information with assumptions to approximate proprietary forecast information, e.g. by inferring high internal information quality from quickly announced earnings (Dierynck and Labro, 2018; Gallemore and Labro, 2015). Studies drawing on genuinely proprietary archival data remain rare and are therefore highly valuable for advancing our understanding of corporate decision-making during NPD (Jordan and Messner, 2020; Wouters and Stadtherr, 2021).

Proprietary archival datasets offer a unique empirical lens on real-world forecasting. Hammann (2024), for instance, combines high-volume archival data with expert interviews to show that machine-learning models trained on big data outperform intermediate datasets and rival traditional expert estimates. Bajari et al. (2019) use proprietary archival data from e-commerce to investigate four hypotheses linking dataset size and *Forecast Accuracy*. Such datasets offer two decisive advantages that lie in their granularity (design attributes, process specifics, technical complexity) and their contextual depth (organizational practices and external volatility).

Capitalizing on such data, this paper empirically examines the determinants of forecast accuracy related to the contribution margin of NPD projects of a major automotive original equipment manufacturer (OEM), referred to as European Car Corporation (ECC). We focus specifically on the accuracy of the contribution margin forecasts rather than on raw cost forecasts, as this is the variable on which decision-makers at our partner company actually act. Studying the contribution margin accuracy therefore captures what is decision-relevant in practice, while building on the closest available theoretical anchor in the cost-forecast literature. The underlying dataset is of proprietary archival nature otherwise not publicly accessible, and its insights are of direct strategic relevance for product development under market volatility.

The remainder of this paper is structured as follows. Section 4.2 provides important background information about the distinct literature streams covering *Forecast Accuracy*. Section 4.3 derives our hypotheses. Section 4.4 describes the research site, available data, and variables. Section 4.5 presents the correlated random effects (CRE) model as well as the results. Section 4.6 concludes the paper.

4.2 Literature Review

During NPD, financial tradeoffs – situations in which two or more financially relevant project objectives cannot be simultaneously optimized, requiring decision-makers to prioritize among competing cost, time, and quality targets following the ideal of an overall profit maximization – are omnipresent (Krishnan and Ulrich, 2001). Understanding what drives forecast accuracy of contribution margins is therefore essential for NPD success. Studies directly analyzing the accuracy of contribution margin forecasts are scant which is why we anchor our research in the literature investigating the accuracy of cost forecast. As the costs directly impact the contribution margin, we reason that potential determinants of the cost forecast literature transmit their effects to the accuracy of contribution margin forecasts. Therefore, we investigate whether project characteristics act as such determinants, drawing on a literature search using the keywords *Forecast Accuracy*, *Cost Overrun*, and *Forecast Error* in conjunction with *Project Management*. The resulting body of work falls into five domains: civil engineering, project management, engineering management, management accounting, and operations management.

Contributions in the civil engineering domain investigating *Forecast Accuracy* of projects mainly address an entire project budget perspective and do not shed light on a specific cost type. Hence, scholars either investigate cost overruns in a general manner or analyze factors that are related to cost contingency. The latter part, that is driven by risk management, forms the smaller share of research (Thal et al., 2010). Sonmez et al. (2007), for example, link classified risk factors to contingency costs in 26 construction projects. Flyvbjerg et al. (2003, 2002) document significant budget excesses for rail, fixed links, and road projects worldwide, and identify project size effects. Both sub streams link project characteristics, e.g. project size, or communication of project teams, to aggregate budget outcomes (Xie et al., 2022). We differ by examining how product characteristics (production strategy, segment) affect the accuracy of contribution margin forecasts.

Relevant contributions belonging to the domain of project management are on their side often related to the civil engineering discipline. Accordingly, Frimpong et al. (2003) investigate the causes of delay and cost overruns in construction of groundwater projects in Ghana. Based on construction projects, but with a more nuanced view on the individual project lifecycle stages is the contribution of Doloi (2011). The author contributes a concept model criticizing cost estimation in the early phase, the cost discussions in the tendering phase, and the control of costs in the project initiation phase.

Contributions corresponding to the discipline of engineering management are mostly concerned about the technical aspects behind cost estimation (Hammann and Wouters, 2025). Technical aspects refer to the quantitative cost estimation approaches being either parametric using defined cost drivers or analytical based on operations, broken-down resources, detailed design information to assess cost tolerances, features, or activities. Besides, qualitative cost estimation endeavors are either based on analogy or intuition from rules, logics, or experts (Niazi et al., 2006). Altavilla et al. (2018) extend the review of Niazi et al. (2006) via a multilayer framework that also considers technique nature, analysis type, product features, development phase, and analytical objectives. Qian and Ben-Arieh (2008) show that different estimation methods apply at different development stages: activity-based methods gain accuracy with detail, while simpler early-stage methods remain acceptable.

Publications belonging to the management accounting domain are driven by a motivational perspective assuming that individuals tend to bias forecasts actively in their favor (Jordan and Messner, 2020). The classical principal agent framework exemplifies this view (Jensen and Meckling, 1976). “Biased budgeting” (Lukka, 1988, p. 282) captures a deliberate gap between an actor’s honest estimate and the submitted figure, prompting proposals for ownership and incentive alignment. Brüggen and Luft (2016, pp. 793–794) subdivide the contributions concerning “Forecast Accuracy”, “Forecast Errors”, and “Cost Overruns” belonging to the management accounting domain into two substreams of research, namely “Capital Budgeting” – e.g. Haka (2007) or Kenno et al. (2018) – and “Escalation of Commitment” – e.g. Sleesman et al. (2012). From a capital budgeting perspective, slack and inaccurate forecasts are motivated by the intended ease of realizing financial targets as well as the ability to secure more project-allocated resources (Davila and Wouters, 2005). Besides, nature of the management accounting information plays a role in decision-making and therefore in resolving financial tradeoffs during NPD (Magnacca and Giannetti, 2024). The quality of management accounting information, e.g. the accuracy of cost forecasts, plays also an important role in cost effective design and taken decisions to resolve financial tradeoffs that are present during product development (Chwastyk and Kołosowski, 2014). From a behavioral accounting perspective, the precision of information affects the honesty and transparency in sharing information (Abdel-Rahim and Stevens, 2018; Hannan et al., 2006). In an experimental setting, Booker et al. (2007) distinguish between two kinds of cost information – specific referring to exact costs measured in dollars, and relative measured by comparing design options in stating which one is more expensive. Thereby, they find that specific cost information generally leads to more cost-effective designs (Booker et al., 2007). Gopalakrishnan et al. (2015) find that the NPD process environment – sequential or concurrent – affects the benefits that result from having specific cost goals on a company's cost reduction performance.

Besides, operations management-based contributions analyze *Forecast Accuracy* mostly from a qualitative instead of a behavioral perspective. Since accurate forecasts are primarily seen as facilitator and key requirement for efficient and effective work, related contributions compare and analyze different forecasting approaches to identify the situation-optimal technique. Tracking accuracy and enforcing its improvement is usually suggested as remedy against inaccurate forecasts (Jordan and Messner, 2020). Danese and Kalchschmidt (2011) show that a structured forecasting process can effectively combine quantitative techniques with managerial knowledge to improve performance.

4.3 Hypothesis Development

4.3.1 Time Effects

H_1: Project progress over time is positively related to the contribution margin forecast accuracy.

Project progress over time measures how advanced a project is in its development process, i.e. how close it is to complete the development process to be sold as finished product on the market. We base our hypothesis on arguments found in the literature regarding an increased data availability over time (Dahan and Hauser, 2002), reduced uncertainty over time (Voltolini et al., 2019), refinement and learning effects due to larger amounts of data known as the "data feedback loop" (Bajari et al., 2019, pp. 33–34), and more sophisticated forecasting approaches that become usable in more advanced NPD stages closer to the finalization of the development process (Qian and Ben-Arieh, 2008).

Empirical research on this relation is limited because the relevant proprietary data is rarely accessible (Ballesteros-Pérez et al., 2020a). The contributions of Ballesteros-Pérez et al. (2020a, 2020b) form notable exemptions as they analyze datasets comprising over 100 construction projects. In their first study, the authors find a significant improvement between the initial cost estimates and final forecasts (Ballesteros-Pérez et al., 2020b). Their second study extends their initial findings as the authors find that there exists a significant positive trend in their dataset between the first, the ultimate and all in-between forecasts. Hence, the authors model the estimates as a function of the completed activities – i.e. a correlated variable with development time – via a lognormal distribution. Thereby, Ballesteros-Pérez et al. (2020a) show that over time, the forecasts become significantly more accurate.

4.3.2 Production Effects

H_2: Contribution margin forecast accuracy is higher for internally manufactured products than for externally manufactured ones.

We base our hypothesis on arguments found in the literature regarding supply chain visibility (Johnsen, 2009; Ragatz et al., 2002), and operational responsiveness (Danese and Kalchschmidt, 2011). Accordingly, Johnsen (2009) summarizes the state of knowledge concerning supplier involvement that important suppliers need to be involved as early as possible to maintain control over externally sourced parts. Hence, a lack of control and information about the development process reduces the quality of forecasts. Internal production gives access to more diverse information than supplier-provided data, which facilitates structured forecasting and boosts accuracy. (Dierynck and Labro, 2018). Danese and Kalchschmidt (2011) analyze the role of the forecasting process in improving *Forecast Accuracy* and operational performance by using data of 343 distinct manufacturing companies. Accordingly, having a structured forecasting process can effectively blend quantitative techniques with the knowledge and experience of management to achieve better performance. Internal production gives access to more diverse information than supplier-provided data, which facilitates structured forecasting and boosts accuracy.

4.3.3 Segment Importance

H_3: Segment importance is positively related to the contribution margin forecast accuracy.

In product portfolio research, importance has been described along several dimensions, including economic relevance (revenue and contribution-margin weight), strategic salience (flagship status, brand-defining role, halo effects on neighboring products), and technical density (engineering complexity and innovative content) (Bentzen et al., 2011). We operationalize *Segment Importance* through sales volume for the following reasons. First, sales volume most directly determines a segment's economic weight as a given per-unit contribution margin scales linearly with units sold, and decisions on plant allocation, supplier negotiation, and capital investment at ECC are explicitly anchored in expected sales volume. This is consistent with the broader operations-management practice of allocating forecasting effort and review intensity by economic weight, e.g. the logic underlying ABC classification and Pareto-based forecast prioritization (Davydenko and Fildes, 2013; Syntetos et al., 2009). Second, sales volume is observable, objective, and directly available in the archival dataset. Alternative proxies, such as strategic salience, flagship status, or brand-building intent, would require subjective coding that we cannot reproducibly perform from the archival management-accounting data at hand which would raise validity concerns. We acknowledge, however, that this proxy may be incomplete. Low-volume segments may carry high strategic importance through brand-defining flagship products and halo effects on neighboring segments (Heitmann et al., 2020).

The hypothesis predicts that the cross-sectional accuracy of contribution margin forecasts increases with a segment's sales volume, on the premise that volume captures the dominant share of variation in management attention to forecast quality. We base the positively postulated relation of our hypothesis on arguments found in the literature regarding the additional effort put into forecasts once they serve as baseline for decisions (Gartner and Thomas, 1993) as well as judgmental interventions on forecasts of strategically important products (Davydenko and Fildes, 2013; Fildes et al., 2009). Besides, high-importance products are characterized by a strong devote of management attention through time, focus, and effort (Ocasio, 1997). Accordingly, the higher the management attention, the higher the justification for decisions and hence the lower the uncertainty (Riedl et al., 2013; Wouters et al., 2009).

The survey-based empirical contribution of Gartner and Thomas (1993) finds a significant positive correlation between a decision-makers conviction of investing efforts into forecasts to use them as a baseline for sustained decisions and the accuracy of the generated forecasts. Accordingly, once more effort is invested into generating forecasts, their accuracy increases which is based on the perceived importance of forecasts. Importance as such may be driven by personal beliefs as Gartner and Thomas (1993) operationalize it but also by corporate key figures that drive the decision-making principles within a corporation. In this respect, research on managerial adjustments to demand forecasts in supply chains shows that planners frequently devote additional effort and judgmental interventions to forecasts of strategically important products (Davydenko and Fildes, 2013; Fildes et al., 2009). Focusing on sourcing decisions, the field study of Wouters et al. (2009) as well as the empirical analysis of Riedl et al. (2013) find that high attentive senior management asks for more detailed information to improve decision-making.

4.4 Research Method

4.4.1 Research Site

We were given the unique opportunity to work as an active member of ECC’s management accounting department over a period of three years gaining firsthand experience at a large-scale automotive OEM and access to a sensitive financial information rarely found in case studies (Jönsson and Lukka, 2006; Lukka and Wouters, 2022; Suomala et al., 2014). The dataset captures key financial information of 43 NPD projects that have successfully completed their individual product development processes to reach their start of sales and market launch. The dataset comprises financial as well as strategic information on the individual projects over a total time span of three and a half years equaling seven timepoints. Each calendar year possesses two timepoints whereas the first one is of March and the second one is of September of the respective years. Additionally, the dataset possesses observed financial information at the market launch of every product. We accessed the data of these diverse projects via the main management accounting database that is used to track and steer central project key performance indicators such as the contribution margin (CM) at the product level. Accessing the data from a single source ensures comparability of the individual projects on a numerical level without the need to further adjust the dataset and covers the risk of flaws in our analysis activities due to diverging data generation methods.

As this research uses a proprietary archival dataset, we present our findings on a disguised basis to ensure confidentiality whilst preserving the substance of the data at hand. To anonymize the dataset no exact project names or times are reported – both the project and time identifiers are denoted by random numbers with no possibility to be back-tracked to the real project and time information. Besides, the dependent variable is calculated in absolute terms to disguise whether the contribution margins were forecasted too positively or negatively. Instead, only an absolute deviation is used, which as such is on its side the result of a terms of differences as we will show in section 4.4.3.1. Hence, by reporting only the absolute result of a metric that is dependent on distinct steering parameters, e.g. cost and revenue, we do not report any information that could be used to reverse engineer the confidential steering parameters. Moreover, as we show in section 4.4.3.2, the independent variables are dummy variables that do not reveal information such as the exact place of production or the body style being a high- or flat-floor vehicle.

4.4.2 Forecasts and Realized Data at European Car Corporation (ECC)

The most important financial performance indicator during NPD for decision-makers at our partner company is the CM on the product level. The dataset distinguishes two CM types, each observed in two states, yielding four distinct values.

In our dataset there are two types of CM values, one being based on the actual product, its expected retail price and actual direct costs, and one being based on the corporate return targets as well as the restricted allowable direct cost basis. We refer to the former kind of value as an *Actual* value, whereas we refer to the latter one as a *Target* value. The actual values are calculated by deducting all direct costs (DC) (e.g. direct material costs, or transportation costs of finished cars) of the product from its total net revenue (NR) which equals the products attainable retail price (ARP) minus dealer margins, taxes, and import respectively export fees.

$$CM_{Actual} = NR - DC = ARP - Dealer\ Margin - Taxes - Import\ and\ Export\ Fees - DC$$

The target values are derived from an increasing function of the products' NR, which is linked to the corporate financial goals of return on sales and return on investment. The target CM just fulfills these corporate goals from a cascaded product perspective.

$$CM_{Target} = f(NR)$$

Besides, there are two states at which the values are obtained, one being during the development of the product – referred to as predicted and planned values – and one being at the market launch – referred to as observed and definite values. Accordingly, we distinguish four different CMs, a *Predicted Actual*, an *Observed Actual*, a *Planned Target*, and a *Definite Target*. These are important for the operationalization of our dependent variable in the next section. We emphasize this richness of our dataset as a unique quality which as such marks an added value to the literature.

As illustrated by Figure 27, all decisions and assessments within the company at a certain point in time are made based on the difference between an actual and a target value. This dual structure – each timepoint carrying both an actual and a target – is what makes the dataset unusually rich.

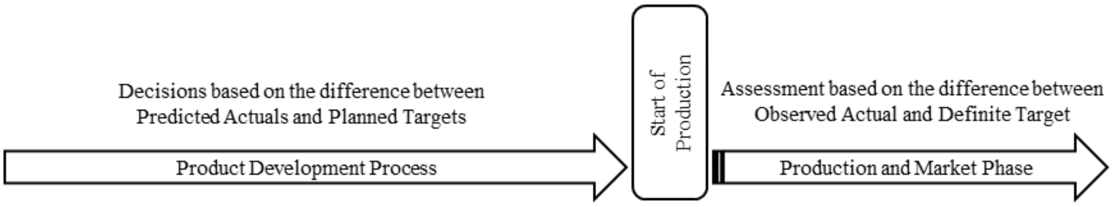

Figure 27 – Graphical Illustration of the Data along the Product Development and Product Market Phase

To make these four terms of values more understandable we use a fictional example as follows. Assume there is a product that has the following CM data as outlined in Table 22.

Table 22 – Example to Illustrate the Different Value Dimensions of our Archival Dataset – Disguised Data

Value Dimension	Time 1	Time 2	Time 3	Market Launch and Start of Sales	Value Dimension	Time T
Actual	5000 EUR	5800 EUR	6200 EUR		**Actual**	6700 EUR
	Predicted	***Predicted***	***Predicted***			***Observed***
Target	8000 EUR	7800 EUR	7500 EUR		**Target**	7200 EUR
	Planned	***Planned***	***Planned***			***Definite***

At Time 1, the product was predicted to reach an CM of 5,000 EUR against a required 8,000 EUR – a 3,000 EUR shortfall under the forecast. At market launch, the realized CM is 6,700 EUR against a required 7,200 EUR – a 500 EUR shortfall. A ECC cost expert summarizes:

"At timepoint one, we needed a CM of 8,000 EUR while we expected to reach a CM of 5,000 EUR only. Now at timepoint T, we realized a CM per product of 6,700 EUR while a desirable CM would be 7,200 EUR per product."

4.4.3 Variable Measurement

4.4.3.1 Dependent Variable: Forecast Accuracy

We operationalize *Forecast Accuracy* through the forecast error[2] (FEr_t), a scale-dependent measure of the difference between realized and forecasted values at time *t*. The closer the FEr_t is to zero, the more accurate the forecast (Buturac, 2022; Hyndman and Koehler, 2006). The use of FEr_t is motivated by practice, as it is an easy-to-understand metric that represents the decision-making basis at our partner company and is as such mostly found in case study research (Ano and Martinez-de-Albeniz, 2023).

To calculate the FEr_t, we use the general error formula of Hyndman and Koehler (2006) modified to consider absolute terms, where e_t defines FEr_t, Y_t denotes the observation at time t and F_t denotes the forecast at time t, thus:

[2] The forecast error is also known as prediction error (Ano and Martinez-de-Albeniz, 2023).

$$e_t = |Y_t - F_t|$$

Considering our dataset with four different CM values, this formula transforms into the following equation:

$$FEr_t = |(Observed\ Actual_T - Definite\ Target_T) - (Predicted\ Actual_t - Planned\ Target_t)|$$

FEr_t compares the ultimately observed actual–target gap with the gap forecasted at time t. When both gaps coincide, the FEr_t equals zero indicating a perfectly accurate forecast. Applied to the fictional example from section 4.4.2 at timepoint 1, the *FEr* at timepoint one (FEr_1) calculates as follows.

$$FEr_1 = |(Observed\ Actual_T - Definite\ Target_T) - (Predicted\ Actual_1 - Planned\ Target_1)|$$

$$FEr_1 = |(6{,}700\ EUR - 7{,}200\ EUR) - (5{,}000\ EUR - 8{,}000\ EUR)|$$

$$FEr_1 = 2{,}500\ EUR$$

4.4.3.2 Independent Variables: Time, Production Effects, Segment Importance

We use three independent variables: *Time Effects*, *Production Effects*, and *Segment Importance*. *Time Effects are* an individual-invariant regressor (same values across subjects, changing over time). *Production Effects* and *Segment Importance* are varying regressors (changing both across subjects and, potentially, within subjects over time). We do not use any time-invariant regressors (diverging between subjects but constant for each subject over time) (Stoetzer, 2020).

Time Effects

We capture *Time Effects* through seven binary dummies d_time_t indicating the timepoint of each forecast. The forecasts are made on a reoccurring basis and updated every half year with a strategic time horizon of five to ten years. In these planning rounds, decisions on plant allocation and the distribution of investments across diverging new models are made or re-adjusted. The lowest indexed dummy variable d_time_1 refers to the earliest forecasts whereas d_time_7 indicates the latest forecasts respectively. Accordingly, the corresponding dummy variable d_time_t is defined as follows.

$$d\_time_t = \begin{Bmatrix} 1, if\ time = t \\ 0, else \end{Bmatrix}$$

$$Range: [1; 7]\ \forall t \in \mathbb{N}$$

Production Effects

We capture *Production Effects* on *Forecast Accuracy* through a binary indicator for inhouse manufacturing. As we face a dataset that mainly contains data during the planning stages, the indication of whether a project is about to be produced internally is subject to change. Accordingly, we use the variable $d\_ownprod_l$ that is defined as follows.

$$d\_ownprod_l = \begin{Bmatrix} 1, if\ product\ is\ (planned\ to\ be)\ produced\ internally \\ 0, else \end{Bmatrix}$$

Segment Importance

We distinguish five classes of vehicles ranging from small cars to luxury vehicles. As baseline, we group the cars within our dataset according to the segment classification scheme proposed by the European Commission (EC) as well as the European Automobile Manufacturers' Association (ACEA). Generally, the segmentation logic is based on diverse criteria such as – among others – vehicle dimensions, vehicle equipment, the retail price, or the brand perception (European Commission, 1999). To avoid definitional ambiguity, we do not split segments by body style (e.g. passenger car vs. SUV): our segmentation is purely size-based. For our segment definition, we use five dummies d_rank_j, whereby we define that the volume-wise best-selling segment receives the first of the indexed dummy variables. This conforms with our postulated hypothesis which defines that the importance of a segment is in our case defined by the sales volume as this secures the utilization of factory capacities and the product level financing of high development costs for a modularly built product family architecture. Hence, the most important segment Gamma receives the indexed rank one, and the least important segment Epsilon receives the indexed rank five. Table 23 provides an overview.

$$d\_rank_j = \begin{Bmatrix} 1, if\ Segment = j \\ 0, else \end{Bmatrix}$$

$$Range: [1; 5]\ \forall j \in \mathbb{N}$$

Table 23 – Overview Vehicle Segmentation

Literature		**Example**	**Case Company**	**This Study**	
Segment according to the EC (1999)	**Segment according to the ACEA (2024)**	**Description**	**Average Sales Volume per Year**	**Sales Volume based Segment Classification used in this study**	***d_rank_j***
A	Small	City cars, e.g.: Fiat 500, Opel Adam	130,000	*Alpha*	4
B	Small	Small cars, e.g.: Renault Clio, Ford Fiesta			
C	Lower Medium	Medium cars, e.g.: Volkswagen Golf, Honda Civic	310,000	*Beta*	2
D	Upper Medium	Large cars, e.g.: BMW 3-Series, Volkswagen Passat	340,000	*Gamma*	1
E	Luxury	Executive cars, e.g.: Audi A6, Mercedes CLE	200,000	*Delta*	3
F	Luxury	Luxury cars, e.g.: Mercedes S-Class, BMW 7-Series	30,000	*Epsilon*	5
S	-	Sport coupes, e.g.: Porsche 911, Audi R8			

4.5 Data Analysis

4.5.1 Descriptive Results

The dataset contains in total 266 datapoints distributed over a timeseries of seven periods. To get a more nuanced understanding of the dataset at hands, we present descriptive statistics for the entire dataset but also clustered by the independent variables that we refer to as "Grouping Category" in Table 24.

Table 24 – Summary Descriptive Statistics for FEr_t – Disguised Data.

Grouping Category	N	Mean (EUR)	Median (EUR)	Standard Deviation
		Total Sample		
Entire Dataset	266	2,010.69	1,240.71	2,351.31
		Time Effects		
Timepoint 1	33	1,946.95	1,432.54	2,545.54
Timepoint 2	33	1,847.28	1,158.43	2,454.91
Timepoint 3	43	2,488.14	1,340.31	2,890.63
Timepoint 4	40	2,102.97	1,211.58	2,745.42
Timepoint 5	43	2,266.34	1,419.41	1,995.29
Timepoint 6	37	1,688.31	1,190.40	1,782.21
Timepoint 7	37	1,583.94	1,086.94	1,778.63
		Production Effects		
External Production	71	2,557.79	1,690.56	2,648.89
Internal Production	195	1,811.49	1,091.13	2,207.00
		Segment Importance		
Segment *Gamma*	88	1,565.77	1,102.74	1,550.60
Segment *Beta*	60	1,330.17	1,167.26	1,048.46
Segment *Delta*	90	2,868.74	1,659.61	3,020.64
Segment *Alpha*	16	244.30	198.00	270.26
Segment *Epsilon*	12	4,595.92	3,650.26	3,520.22

Concerning our independent variables, the following characteristics deserve attention. Regarding the *Time Effects* in our analysis out of 43 projects, 31 have observations at all seven timepoints. The remaining 12 have between two and six observations, with three projects (IDs 35, 98, 169) showing missing data at timepoint four attributable to random missingness in the proprietary data. Our panel is therefore unbalanced (266 of a theoretically maximum 301 datapoints[3]) and classifies as short (T < 20), which reduces concerns about autocorrelation but heightens concerns about heteroscedasticity (Cameron and Trivedi, 2015; Torres-Reyna, 2007; Wooldridge, 2013). The FEr_t across time is rather equally split with the most inaccurate forecasts made on average at timepoint three and at median at timepoint one. The most accurate forecasts were on average and on median made at timepoint seven. Also, the quantity of datapoints per time dummy is with a range of 33 to 43 observations rather equally split across the dataset.

Concerning the *Production Effects*, the FEr_t is on average and median smaller once the products are manufactured at internal company site. Thereby, almost every third out of four datapoints relates to projects planned to follow an internal production strategy.

[3] In a balanced panel, the total amount of data entries equals the product of the amount of subjects' times the amount of time points, in our case the product of 43 project * 7 timepoints = 301 data entries.

Concerning the *Segment Importance*, the number of observations is quite unequally distributed with Gamma and Delta having by far the largest number and Alpha and Epsilon having the lowest one. Based on our hypothesis, Gamma and Beta should have the most datapoints as these segments are the highest sold ones. Unfortunately, several Gamma and Beta projects were close to, but had not yet reached, market introduction when the data were extracted. Hence, these datapoints are missing in the dataset, which would have increased their weight. The underrepresentation of Gamma and Beta relative to their sales volume should be kept in mind when interpreting the segment findings.

Finally, the variance of the independent variables over time is highly heterogeneous, which matters for model selection. Time dummies vary fully by construction. Production and segment, however, vary only through strategic shifts. 16 of 43 projects have a switch in production strategy, only 8 of 43 are considered for more than one segment.

4.5.2 Statistical Model – Option

Panel data – repeated observations of cross-sectional units over time – require models that address within-unit correlation, unobserved individual heterogeneity, and efficiency losses from omitted variables. Ordinary least squares (OLS) which treats all observations independently, produces wrong standard errors, incorrect significance tests, and – when unobserved individual effects correlate with regressors – biased coefficients. It also fails to exploit the repeated-measures structure of the data. The three standard alternatives are the pooled, fixed-effects, and random-effects models. A fourth possibility (discarded by us) – the between estimator – collapses the time variation into a single per-unit observation and always yields worse results than the random-effects estimator (Wooldridge, 2013).

The three models differ in their treatment of the error term (Wooldridge, 2013).

- Pooled models assume errors are independent across all observations and estimate by OLS. This assumption rarely holds in practice (Stoetzer, 2020).
- Fixed and random effects models decompose the error into an unobserved time-invariant individual effect a_i and an idiosyncratic noise term u_{it}:

$$\varepsilon_{it} = a_i + u_{it}$$

Fixed effects (FE) models eliminate a_i by transformation – i.e. by first differences, least-squares dummy regression, or within-demeaning – and then estimate by OLS, removing omitted-variable bias from time-invariant individual characteristics. A drawback is that time-invariant covariates are wiped out alongside a_i (Stoetzer, 2020).

Random effects (RE) models are mathematically more complex as they require the use of generalized least squares (GLS) instead of OLS. They treat a_i as random and uncorrelated with the regressors – an assumption testable via the Hausman test. If maintained, random effects yield lower standard errors and admit time-invariant covariates (Stoetzer, 2020; Wooldridge, 2013).

4.5.3 Statistical Model – Selection and Assumptions

To choose the right panel regression model, Stoetzer (2020) presents a three step process which we will follow[4]. Hence, the following decision rules apply.

i) Fixed effects or pooled model: Decision based on the F-test, whose null-hypothesis postulates that the constant terms of all individuals are identical and hence checks for the significance of fixed effects. If the null hypothesis is rejected, there is no pooled model applicable and fixed effect models should be used.
ii) Random effects or pooled model: Decision based on the Breusch-Pagan-Lagrange-Multiplier (BPLM) test, whose null-hypothesis postulates that the project specific as well as the idiosyncratic variance do not systematically deviate from zero. If the null hypothesis is rejected, there is no pooled model applicable and random effect models should be used.
iii) Fixed effects or random effects model: Decision based on the Hausman Test, whose null-hypothesis postulates that there are no significant differences in the results of conducting a fixed effects and a random effects regression. If the null hypothesis is rejected, the random effects model yields inconsistent results and a fixed effects model should be applied.

Step (i): We run the F-test including six time dummies[5] and suppress clustered standard errors as otherwise Stata would not show us the F-test result. We retrieve an F statistic of 4.76 that is significant at the 99 percent level. Accordingly, we reject the null hypothesis that postulates that the coefficients for all years are jointly equal to zero (Torres-Reyna, 2007), which makes a fixed effects model preferable over a pooled one. Table 25 presents the regression output.

Table 25 – F-test – Decision Between a Fixed Effects (FE) and a Pooled Model

F-test that all u_i=0: F(42, 212) = 4.76	Prob > F = 0.00

Step (ii): We run a random effects regression and conduct the BPLM test via the Stata command `xttest0`. As Table 26 denotes, we reject the null hypothesis at the 1%-level indicating significant differences between the project specific as well as the idiosyncratic variances. Therefore, a random effects model is preferable over a pooled one.

Table 26 – Breusch-Pagan-Lagrange-Multiplier-Test (BPLM) Test – Decision Between a Pooled and a Random Effects (RE) Model

Breusch-Pagan LM Test χ^2=89.09	Prob > χ^2 = 0.00

[4] The proposed selection process of Stoetzer (2020) provides a practicable heuristic to choose among different theoretically available regression techniques for panel datasets. A detailed explanation and further tests is provided by Baltagi (2021). Since it is a decision heuristic, the outcome is only a very good indication. Individual circumstances may justify the use of an alternative regression setup (Stoetzer, 2020).
[5] We drop the seventh time dummy to avoid multicollinearity.

Step (iii): The standard Hausman test assumes efficient random-effects estimators, which fails under the cluster-robust standard errors that we use to handle heteroscedasticity (Cameron and Trivedi, 2010). Therefore, we use the Mundlak test – operated in Stata via the `estat mundlak` command (Perales, 2013) – that characterizes an alternative robust test statistic (Stata Corporation, 2025a). The null hypothesis for the Mundlak test proclaims that the coefficients on these group-mean variables are jointly zero, also indicating no correlation between the unobserved individual effects and the regressors (Wooldridge, 2002). As Table 27 denotes, the results provide strong evidence against the null hypothesis that the RE model is correctly specified. Therefore, we reject the null hypothesis which implies that a fixed effects model is the preferable choice for the analysis.

Table 27 – Mundlak (1978) Specification Test – Decision Between a Fixed Effects (FE) and Random Effects (RE) Model

Mundlak Specification Test χ^2 =68.76	Prob > χ^2 = 0.00

Reconsidering the low variability of production and segment effects over time characterizes an issue in the model selection: if we would blindly choose a classic FE model, only those datapoints would be considered that change from one observation to the consecutive one, the rest would be disregarded (Torres-Reyna, 2007). We therefore adopt a correlated random effects (CRE) model, which retains the random-effects mechanics but adds time-averaged regressors, allowing fixed-effects-consistent estimation for both time-variant and time-invariant predictors. (Allison, 2009; Mundlak, 1978; Wooldridge, 2025, 2019).

To set up the chosen CRE model correctly, several assumptions must be fulfilled as summarized in Table 28.

Table 28 – Correlated Random Effects (CRE) Regression Model Assumptions, based on Wooldridge (2013, pp. 509–511)

Assumption	Explanation
#1	**Linear Model Specification:** For each *i*, the model is: $y_{it} = \alpha + ß^W x_{it} + \gamma \bar{x_i} + r_i + u_{it} \quad t = 1, \dots, T$ where $ß^W$ and γ are the parameters to estimate and r_i as well as u_{it} form the error component.
#2	**Random Sampling:** We have a random sample from the cross section.
#3	**Multicollinearity:** No perfect linear relationships exist among the explanatory variables.
#4	**Strict Exogeneity and Mean Independence of the Unobserved Effect:** For each *t*, the expected value of the idiosyncratic error given the explanatory variables in all time periods and the unobserved effect is zero: $E(u_{it}\|X_i,a_i) = 0 \quad t = 1,...,T.$ Besides, the expected value of r_i is constant: $E(r_i\|X_i) = ß_0$
#5	**Homoscedasticity:** $Var(u_{it}\|X_i,r_i) = Var(u_{it}) = \sigma^2_u$ for all t = 1,...,T. $Var(r_i\|X_i) = \sigma^2_r$
#6	**No Autocorrelation:** For all $t \neq s$, the idiosyncratic errors are uncorrelated (conditional on all explanatory variables and r_i): $Cov(u_{it},u_{is}\|X_i,r_i) = 0$
#7	**Normality:** Conditional on X_i and r_i, the u_i are independent and identically distributed as $Normal(0, \sigma^2_u)$

Assumption #1 – Linear Model Specification

Our estimating equation takes the form prescribed in Table 28. More detailed, in a CRE model, three distinct effects of interest per regressor could be distinguished (Bell and Jones, 2015; Schunck, 2013):

- The within effect – denoted by $ß^W$ – estimates how changes in a variable within the same unit relate to changes in the outcome, controlling for all time-invariant heterogeneity.
- The between effect – denoted by $ß^B$ – captures the cross-sectional association between a unit's time-averaged regressor and its time-averaged outcome, including unobserved unit-level characteristics.
- The contextual effect – denoted by γ – measures the divergence between within- and between-unit relationships.

Accordingly, we formulate the following CRE research model to investigate the influence of our explanatory variables on FEr_t. Therefore, we employ the general formula as presented by Wooldridge (2013), where α is the intercept, $ß^W$ are the within effects of the panel regression model, γ are the contextual coefficients describing the difference of the between ($ß^B$) and within ($ß^W$) effects in the panel regression, r_i is the time-invariant individual (project) effect, and u_{it} is idiosyncratic random noise. The x_{it} characterizes the independent variables over time and the $\overline{x_i}$ describes the time average thereof (Schunck, 2013). Besides, this formula serves as baseline for the `xtreg, cre` command in Stata that we use to estimate our postulated hypotheses and which we will refer to as main model (Stata Corporation, 2025b).

$$y_{it} = \alpha + ß^W x_{it} + \gamma \overline{x_i} + r_i + u_{it}$$

$$y_{it} = \alpha + ß^W x_{it} + (ß^B - ß^W)\overline{x_i} + r_i + u_{it}$$

Adapted to our research purpose – by using the variables as explained in section 4.4.3 and dropping the last time as well as first segment dummy to avoid multicollinearity – this formula transforms to the following equation.

$$FEr_{it} = \alpha + \sum_{k=1}^{6} ß_k^W * d_{time_{k,it}} + \sum_{k=1}^{6} \gamma_k * \overline{d_{time}}_{k,i} + ß_7^W * d_{ownprod_{it}} + \gamma_7 * \overline{d\_ownprod}_i + \sum_{j=8}^{11} ß_j^W * d\_rank_{j,it} + \sum_{j=8}^{11} \gamma_j * \overline{d\_rank}_{j,i} + r_i + u_{it}$$

An alternative notation serving as baseline for the Stata command `xthybrid` is the equation of Schunck and Perales (2017) that we use to control our regression results and which we will refer to as control model.

$$y_{it} = \alpha + ß^W (x_{it} - \overline{x_i}) + ß^B \overline{x_i} + r_i + u_{it}$$

The specification therefore conforms with the first assumption of Wooldridge (2013).

Assumption #2 – Random Sampling

The second assumption requires that the cross-sectional units are drawn at random from the population of interest. Our population is defined as NPD projects of the focal automotive OEM in segments Alpha through Epsilon during the observation window. The 43 projects in our dataset comprise all eligible projects in this window. Accordingly, there is no analyst-driven filtering, no self-selection by participants (the data is archival rather than survey-based), and no eligibility criterion beyond the segment definition. The sample is therefore a census of the targeted population and conforms with assumption two.

Assumption #3 – Multicollinearity Requirement

The third assumption requires the absence of perfect linear relationships among the explanatory variables. Since multicollinearity is always present to some degree and cannot be fully avoided, it must be kept at moderate levels (Backhaus et al., 2021). A first check uses the Bravais-Pearson correlation matrix between the independent variables, where pairwise correlations above 0.8 signal multicollinearity. Table 29 reports the matrix.

Table 29 – Bravais Pearson Correlation Matrix of Explanatory Variables

Variables	**Label**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
(1) $d\_own\text{-}prod_1$	Dummy for inhouse production	1.00												
(2) d_rank_1	Dummy for segment *Gamma*	**0.14****	1.00											
(3) d_rank_2	Dummy for segment *Beta*	**0.12****	**-0.38*****	1.00										
(4) d_rank_3	Dummy for segment *Delta*	**-0.25*****	**-0.50*****	**-0.39*****	1.00									
(5) d_rank_4	Dummy for segment *Alpha*	-0.10	**-0.18*****	**-0.14****	**-0.18*****	1.00								
(6) d_rank_5	Dummy for segment *Epsilon*	**0.13****	**-0.15****	**-0.12***	**-0.16****	-0.05	1.00							
(7) d_time_1	Dummy for timepoint one	**-0.24*****	-0.02	0.07	-0.05	0.00	0.03	1.00						
(8) d_time_2	Dummy for timepoint two	**-0.24*****	-0.05	0.07	-0.03	0.00	0.03	**-0.14****	1.00					
(9) d_time_3	Dummy for timepoint three	**0.10***	-0.03	0.03	-0.01	-0.03	0.05	**-0.17*****	**-0.17*****	1.00				
(10) d_time_4	Dummy for timepoint four	0.09	-0.01	-0.03	0.03	-0.02	0.01	**-0.16*****	**-0.16*****	**-0.18*****	1.00			
(11) d_time_5	Dummy for timepoint five	**0.10***	0.04	-0.04	-0.01	-0.03	0.05	**-0.17*****	**-0.17*****	**-0.19*****	**-0.18*****	1.00		
(12) d_time_6	Dummy for timepoint six	0.07	0.04	-0.06	0.03	0.04	-0.09	**-0.15****	**-0.15****	**-0.18*****	**-0.17*****	**-0.18*****	1.00	
(13) d_time_7	Dummy for timepoint seven	0.07	0.02	-0.03	0.03	0.04	-0.09	**-0.15****	**-0.15****	**-0.18*****	**-0.17*****	**-0.18*****	**-0.16*****	1.00

Significance Levels *** p<0.01, ** p<0.05, * p<0.1, significant coefficients are marked in bold

No pairwise correlation approaches the 0.8 threshold (Akoglu, 2018). However, multicollinearity can also arise from multiple correlations among the regressors despite low pairwise values. We therefore additionally compute variance inflation factors (VIF) and their inverse, tolerance. The VIF describes “how much the variance of the coefficient estimate is being inflated by multicollinearity” (Senaviratna and Cooray, 2019, p. 3). In addition to the VIF, scholars report its inverse value called tolerance, which can be understood as “the percentage of the variance in a given predictor that cannot be explained by the other predictors” (Senaviratna and Cooray, 2019, p. 3). A VIF above 10 or a tolerance below 0.1 typically raises concern (Backhaus et al., 2021; Senaviratna and Cooray, 2019). Table 30 shows that all tolerances exceed 0.54 and all VIFs remain below 1.84, far from the critical thresholds, allowing us to conform with the third assumption.

Table 30 – Tolerance and Variance Inflation Factor (VIF) – Multicollinearity

Variable	Labels	Tolerance	VIF
$d\_ownprod_1$	Dummy for inhouse production	0.76	1.32
d_rank_2	Dummy for segment *Beta*	0.75	1.33
d_rank_3	Dummy for segment *Delta*	0.70	1.43
d_rank_4	Dummy for segment *Alpha*	0.88	1.14
d_rank_5	Dummy for segment *Epsilon*	0.89	1.12
d_time_1	Dummy for timepoint one	0.56	1.80
d_time_2	Dummy for timepoint two	0.56	1.79
d_time_3	Dummy for timepoint three	0.54	1.84
d_time_4	Dummy for timepoint four	0.56	1.78
d_time_5	Dummy for timepoint five	0.55	1.83
d_time_6	Dummy for timepoint six	0.58	1.72

Assumption #4 – Strict Exogeneity and Mean Independence of the Unobserved Effect

The fourth assumption requires the idiosyncratic error u_{it} to be mean-independent of the regressors in all periods conditional on r_i. We test strict exogeneity using Wooldridge's (2002) augmented regression, which adds first-period leads of the regressors and tests jointly for zero coefficients (Su et al., 2016; Wang et al., 2015). The test statistic uses a F-test on the null hypothesis that the coefficients of the lead terms are simultaneously zero. The test yields a F statistic of 1.06 and a corresponding p value of 0.39 which does not allow us to reject the null hypothesis. Therefore, this test provides no statistical evidence against the assumption of strict exogeneity. Table 31 presents the results of the conducted F-Test after Wooldridge (2002).

Table 31 – F-test – Exogeneity

F-test: $F(5, 163) = 1.06$	Prob > F = 0.39

The Wooldridge test (2002) addresses dynamic endogeneity from correlation between current errors and future regressors but only checks the immediately succeeding period (Patrick, 2022). We therefore additionally consider the four logical sources of endogeneity discussed by Brüderl and Ludwig (2019): unobserved time-varying confounders, measurement errors in the regressors, reverse causality, and endogenous selection bias (including collider bias and attrition). Because our data is proprietary archival data and was not gathered specifically for this analysis, we cannot rule out unobserved time-varying confounders entirely. Hence, we flag this aspect as a limitation of the study design. Measurement errors in the regressors are plausible only to a limited extent, as the database is used throughout multiple stages of the product development process and is subject to repeated quality assessments. Reverse causality is not a concern given the directional structure between forecast error and project parameters. Project characteristics such as production strategy and segment are determined prior to the realization of the forecast error and cannot be revised in response to it. Concerning endogenous selection bias, collider bias is not a concern in our specification as we do not condition on variables that are jointly caused by the regressors and the outcome. Attrition is theoretically possible in our setting, as sudden project stops or shifted starts of production may influence the observed product lifecycle of analyzed projects (Baltagi, 2021). Therefore, we acknowledge this as a residual limitation, noting that cluster-robust standard errors at the project level (Cameron and Miller, 2015) partly absorb within-project dependencies induced by such patterns. Besides, the fourth assumption requires that the unobserved project-specific effect is, on average, unrelated to the regressors. CRE handles this assumption by design as it includes the project-level time-averages of the time-varying regressors as additional controls. These averages absorb whatever correlation exists between the unobserved effect and the regressors, so that the remaining error component is uncorrelated with the regressors. Besides the stated limitations of potentially unobserved time-varying confounders or attrition, we conform with assumption four.

Assumption #5 – Homoscedasticity

Concerning the fifth assumption for CRE panel regressions, heteroscedasticity in panel data means that the variance of errors differs across observations. We use a Wald Test designed for short panels which also considers potential issues from having an unbalanced panel structure with the null hypothesis of homoscedasticity across the individuals (Baum, 2024). The test yields a significant p-value of 0.00 which leads us to strongly reject the null hypothesis, as denoted in Table 32.

Table 32 – Wald Test – Heteroscedasticity

Modified Wald Test for groupwise Heteroscedasticity χ^2 =8.90*10^{31}	Prob > χ^2 = 0.00

This result indicates that our dataset faces a problem of heteroscedasticity against which Brüderl and Ludwig (2019) provide three effective remedies: assume a more realistic error structure with the drawback of biasing the results due to made assumptions, use panel robust standard errors, or bootstrap the standard errors. We adopt cluster-robust standard errors at the project level (Cameron and Miller, 2015), which Wooldridge (2013) confirms as the standard CRE remedy. Accordingly, as we use clustered standard errors on the project level, we can conform to fulfil the fifth assumption.

Assumption #6 – No Autocorrelation

The sixth assumption checks whether the idiosyncratic errors are uncorrelated which is also known as test for serial correlation. Among the most popular tests for serial correlation in panel data are the Wooldridge test for autocorrelation as well as the Durbin-Watson test statistic (Wooldridge, 2013). Table 33 denotes the results of the Wooldridge test for autocorrelation, whereafter the null hypothesis of no autocorrelation in the idiosyncratic error terms can be rejected at the five percent level.

Table 33 – Wooldridge Test – Autocorrelation

F-test: $F(1, 41) = 6.28$	Prob > F = 0.02

Accordingly, we face an issue of autocorrelated errors in our dataset. As remedies, the clustered robust standard errors from the fifth assumption do also counteract the bias caused by autocorrelation of the error term (Cameron and Miller, 2015; Wooldridge, 2013). Besides, we are dealing with a short panel having only seven time periods. In such setting, autocorrelation of the error term is generally not a big issue as problems typically only occur for macro panels including at least a timeseries of 20 or more timepoints (Torres-Reyna, 2007). Hence, our actions counteract the naturally given autocorrelation in the idiosyncratic error term of our dataset.

Assumption #7 – Normality

The seventh assumption is stronger than assumptions four to six combined (adding normality of u_i) but is not required for short panels (Wooldridge, 2013). We therefore do not impose assumption seven. With the first six assumptions met, our CRE model is correctly specified as the best available specification for our dataset.

Having chosen the CRE model in appropriate specification, we now translate our hypotheses into expected coefficient patterns, where we distinguish within from between effects according to the variation each hypothesis targets. Given our hypotheses, we focus on within effects for *Time Effects* (H_1 concerns change from period to period) and between effects for *Production Effects* and *Segment Importance* (H_2 and H_3 concern cross-sectional differences, not strategy switches within a project). Concerning our postulated hypotheses, this translates into the following expected relationships. For H_1, with d_time_7 as reference, we expect the remaining coefficients to be positive and significantly larger, since larger within coefficients correspond to larger FEr_t (i.e. less accuracy). For H_2, with external production as reference, we expect a negative between coefficient for inhouse production (lower FEr_t). For H_3, with highest-volume *Gamma* as reference, we again expect the remaining coefficients to be positive and significantly larger (increasing FEr_t).

The dummy-variable specification above is sufficient to test whether each non-reference category differs from the reference. However, it does not by itself test whether the non-reference categories are themselves ordered as the hypotheses predict (Long and Freese, 2014). An exception is H_2, as the production effects themselves are a binary group comparison between internally and externally produced products, where a significant between effect suffices to reject or confirm the postulated hypothesis. For H_1 and H_3 however, further tests to check the postulated orderings are required. Therefore we use pairwise linear-combination tests on adjacent coefficients following the postulated order (Greene, 2018). H_1 predicts a strictly monotone decrease in the within coefficients across the time dummies ($d\_time_1 > d\_time_2 > \ldots > d\_time_6$), and H_3 predicts a strictly monotone increase in the between coefficients across the segment dummies in the postulated volume ordering (Gamma < Beta < Delta < Alpha < Epsilon). Hence, for H_1 the adjacency should be significantly positive, for H_3 significantly negative.

4.5.4 Regression Results

We estimate the CRE model (the *main model*) with project-level cluster-robust standard errors using the xtreg, cre command of Stata (2025c). Since this command reports the within and contextual effects directly, we need to compute the between effects manually using the lincom command in Stata. This command derives correct standard errors from the full variance-covariance matrix and accounts for the covariance between within and contextual estimates. Thereby, the between effects ($ß^{B}$) are computed as the sum of the within ($ß^{W}$) and contextual (γ) coefficients (Schunck and Perales, 2017).

$$ß^{B} = ß^{W} + \gamma$$

To control this manual computation of the between effects, we use the user-written Stata command of xthybrid – referred to as control model – which directly reports the within and between effects at the expense of not reporting the contextual effects (Schunck and Perales, 2017).

Given our hypotheses target either the within effect (H_1) or the between effect (H_2 and H_3) as explained in section 4.5.3, we will only report the individual effects that are of interest for our postulated hypotheses. Table 34 denotes the results.

Table 34 – Summary Regression Results – Disguised Data

Dependent Variable: FEr_t | Forecast Error			**Correlated Random Effects Regression**	
			Main Model via **xtreg, cre** (Stata Corporation, 2025b)	**Control Model via** **xthybrid** (Perales and Schunck, 2021)
Time Effects (Reference Variable d_time_7 | Dummy for timepoint seven)				
Variables	**Label**	**Effect**	**Coefficients (Robust Standard Errors)**	**Coefficients (Robust Standard Errors)**
d_time_1	Dummy for timepoint one	**Within (H_1)**	99.24 (300.94)	99.24 (289.95)
d_time_2	Dummy for timepoint two	**Within (H_1)**	28.37 (320.51)	28.37 (308.80)
d_time_3	Dummy for timepoint three	**Within (H_1)**	715.58 (443.68)	**715.57* (427.48)**
d_time_4	Dummy for timepoint four	**Within (H_1)**	408.23 (483.48)	408.23 (465.83)
d_time_5	Dummy for timepoint five	**Within (H_1)**	464.14 (418.91)	464.14 (403.62)
d_time_6	Dummy for timepoint six	**Within (H_1)**	92.89 (66.39)	92.89 (63.97)
Production Effects (Reference Variable $d\_b\_ownprod_0$ | Dummy for external production)				
$d\_b\_ownprod_1$	Dummy for inhouse production	**Between (H_2)**	**-1518.55*** (545.42)**	**-1520.68*** (525.22)**
Segment Importance (Reference Variable $d\_b\_rank_1$ | Dummy for segment Gamma)				
$d\_b\_rank_2$	Dummy for segment *Beta*	**Between (H_3)**	-110.21 (435.49)	-106.52 (415.65)
$d\_b\_rank_3$	Dummy for segment *Delta*	**Between (H_3)**	1302.06 (942.71)	1306.18 (906.53)
$d\_b\_rank_4$	Dummy for segment *Alpha*	**Between (H_3)**	**-1696.65*** (636.66)**	**-1694.64*** (612.83)**
$d\_b\_rank_5$	Dummy for segment *Epsilon*	**Between (H_3)**	**3357.82*** (1145.65)**	**3349.72*** (1105.01)**
Constant			-570.49 (3684.12)	-528.43 (3555.48)
			Model Statistics (Main Model)	
Observation (N)			266	
Number of Projects (Clusters)			43	
$R^2_{Overall}$			0.24	
$R^2_{between}$			0.44	
R^2_{within}			0.06	

Significance Levels *** p<0.01, ** p<0.05, * p<0.1, significant coefficients and effects of interest concerning our postulated hypotheses are marked in bold. The underscored "b" in the variable naming denotes the between effect component of the variable.

Overall, the CRE model demonstrates solid explanatory power, accounting for 23.60% ($R^2_{Overall}$) of the overall variance in FEr_t. Notably, the variance decomposition reveals that the model explains 43.50% ($R^2_{between}$) of the cross-sectional differences between projects whilst it explains only 5.90% (R^2_{within}) of the longitudinal variation within projects over time. Unfortunately, the explanatory power of our model concerning within effects (H_1) is weak. However, these results do on the other side prove a solid explanatory power of our model to analyze the between effects (H_2 and H_3) of the independent variables.

Concerning our first hypothesis related to the influence of *Time Effects* on *Forecast Accuracy*, we find no support by our main model. In the control model, the dummy concerning period three is significant at the ten percent level indicating that contribution margin forecasts made at period three deviate on average by 715.57 EUR more than the forecasts made in the reference period, i.e the latest time period seven. Whilst this finding supports our postulated relationship, that forecasts become more accurate regarding the pairwise comparison of period three and seven, its significance cannot be confirmed by the main model. Besides, all other operationalized time dummies show an insignificant relationship on the dependent variable FEr_t. Hence, we stress that our dataset does not provide significant evidence from the both models supporting an improved forecast of the contribution margin over time as postulated in hypothesis H_1.

Concerning our second independent variable, we postulated a negative relation of externally sourced products for their *Forecast Accuracy*. The between effect from our main model is statistically significant at the one percent level indicating that internally produced products deviate by 1,518.55 EUR less from their contribution margin forecasts than externally produced ones. This result is confirmed by the hybrid control model which yields a nearly identical estimate of -1,520.68 which is also significant at the one percent level. Hence, the cross-sectional pattern is clear as internally produced projects exhibit forecast errors that are significantly lower than those of externally produced products which supports our postulated hypothesis H_2.

The results concerning the impact of *Segment Importance* on *Forecast Accuracy* provide partly statistically significant results. For the between effects – which are of primary interest concerning H_3 as they capture the cross-sectional differences between segments – we obtain the following pattern. Segment *Beta* is insignificantly different from the reference segment *Gamma*, indicating that products in these two high-volume segments are forecasted with comparable accuracy. Contrary to our postulated hypothesis, segment *Delta* does not exhibit significantly less accurate contribution margin forecasts than the reference segment *Gamma*. Whilst the coefficient is positive and of considerable economic magnitude, there is no statistically significant inference observable. Hence, we cannot confirm that products belonging to segment *Delta* are significantly less accurately forecasted than those of the reference segment. Notably, segment *Alpha* exhibits a highly significant negative between effect of 1,696.65 EUR, indicating that products belonging to this segment are forecasted significantly *more* accurately than the reference segment *Gamma*. This finding, which is confirmed by the hybrid control, contradicts our postulated hypothesis which expected *Alpha* – as a lower-volume segment – to exhibit less accurate forecasts. Contrastingly, the lowest volume segment *Epsilon* exhibits a highly significant positive between effect of 3,357.82 EUR which confirms that these products face substantially less accurate contribution margin forecasts than segment *Gamma*. This result is robust across both the main CRE model and the hybrid control specification.

To complement the dummy-variable estimates and test the postulated orderings directly, we conduct pairwise linear-combination tests on adjacent coefficients following Greene (2018). The tests are performed via Stata's lincom post-estimation command, which constructs the standard error of each linear combination of coefficients using the cluster-robust variance–covariance matrix from the main CRE estimation (Stata Corporation, 2025c). The clustering at the project level is therefore preserved across the adjacency tests. For H_3, the between effect of the *Segment Effects* is constructed as the sum of the within ($ß^{W}$) and the contextual (γ) coefficient (Schunck and Perales, 2017). Each adjacency in Table 35 reports earlier-coefficient minus later-coefficient in the postulated ordering

Table 35 – Summary Adjacency Tests of the Postulated Orderings under H_1 and H_3 – Disguised Data

Hypothesis (effect)	Adjacency	Coefficient (Robust Standard Error)s	Sign matches prediction
H_1 (within)	Dummy for timepoint one − Dummy for timepoint two	70.87 (73.29)	yes
H_1 (within)	Dummy for timepoint two − Dummy for timepoint three	**-687.21** (343.76)**	no
H_1 (within)	Dummy for timepoint three − Dummy for timepoint four	307.35 (412.38)	yes
H_1 (within)	Dummy for timepoint four − Dummy for timepoint five	-55.91 (484.32)	no
H_1 (within)	Dummy for timepoint five − Dummy for timepoint six	371.25 (401.07)	yes
H_3 (between)	Gamma − Beta	110.21 (435.49)	no
H_3 (between)	Beta − Delta	**-1,412.27* (816.06)**	yes
H_3 (between)	Delta − Alpha	**2,998.72*** (1,034.60)**	no
H_3 (between)	Alpha − Epsilon	**-5,054.48*** (1,271.39)**	yes

Significance Levels *** p<0.01, ** p<0.05, * p<0.1, significant coefficients are marked in bold

Because each hypothesis generates a family of related tests, an increased probability of obtaining at least one statistically significant result by pure chance of the family-wise error rate is in principle a concern. Therefore, it is recommended to correct the individual significance thresholds downward when the family of tests is interpreted jointly, for instance by following the approach of Holm (1979). We choose to report raw p-values without applying a multiple-comparisons correction because the conclusions are, in our case, not affected by the correction. For H_3, the two adjacencies on which our interpretation rests are individually significant at the one percent level, with p-values small enough to remain significant under any conventional adjustment following Holm (1979). For H_1, only one adjacency reaches conventional significance on raw p-values, but it carries the wrong sign relative to the prediction.

The H_1 results refine the picture from Table 34. The dummy specification already showed no significant individual within coefficient and the adjacency tests now show that the postulated monotone improvement of contribution margin forecasts over time also fails as a sequence. Three of the five adjacencies carry the predicted positive sign, but none reaches statistical significance with the predicted sign. The only adjacency reaching significance on raw p-values ($d\_time_2 - d\_time_3$, -687.21) carries the wrong sign and therefore does not support H_1. We accordingly find no statistical evidence for monotone improvement of *Forecast Accuracy* over time, neither at the level of contrasts against the t_7 reference nor at the level of period-to-period transitions.

Concerning the H_3 pairwise results, two adjacencies reach significance at the one percent level on raw p-values. The Alpha – Epsilon transition of -5,054.48 EUR confirms the volume hypothesis at the low-volume end. Moving from Alpha to Epsilon means moving to a low-volume, technically dense flagship that combines lower volume, higher complexity, and lower economic salience. However, the Delta – Alpha transition of 2,998.72 EUR reverses the volume hypothesis. Small-car forecasts (Alpha) are markedly more accurate than mid-size-car forecasts (Delta) despite the smaller sales volume of the Alpha segment, leaving Delta − Alpha positive where H_3 predicts negative on a pure volume base.

To verify these patterns, we rerun the CRE model from above via the two commands `xtreg, cre` and `xthybrid` with single ordinal indices instead of the individual dummies. Hence, there is a *time index* taking values 1 through 7, and a segment-rank index taking values 1 through 5 in the postulated importance ordering. Therefore, under H_1, the within coefficient on the time index is expected to be negative (moving towards a later development period) and under H_3, the between coefficient on the rank index is expected to be positive (moving towards a lower-volume segment). The trend specification imposes linearity and is therefore stricter than the pairwise tests. The model is deliberately less rich than the regression reported in Table 34 as it compresses segment dummies into a single ordinal index which imposes monotonicity that the segment data does not follow. We therefore do not interpret the production coefficient in this specification and rely on the main model in Table 34 for the H_2 result. Table 36 reports the trend coefficients on the time and segment indices.

Table 36 – Summary Linear Trend Specification concerning H_1 and H_3

Dependent Variable: FEr_t | Forecast Error			Correlated Random Effects Regression	
			Main Model via `xtreg, cre` (Stata Corporation, 2025b)	**Control Model via** `xthybrid` (Perales and Schunck, 2021)
Trend *Time Effects*				
Variables	**Label**	**Effect**	**Coefficients (Robust Standard Errors)**	**Coefficients (Robust Standard Errors)**
time_idx (1–7)	Ordinal Time Index (Timepoint one – seven)	**Within (H_1)**	-62.76 (70.91)	-62.76 (70.11)
Trend *Segment Importance*				
rank_idx (1–5)	Ordinal Rank Index (Gamma, Beta, Delta, Alpha, Epsilon)	**Between (H_3)**	**631.53** (248.36)**	**629.26*** (243.56)**
Constant			3251.87 (4900.37)	3262.47 (4861.22)
			Model Statistics (Main Model)	
Observation (N)			266	
Number of Projects (Clusters)			43	
$R^2_{Overall}$			0.09	
$R^2_{between}$			0.20	
R^2_{within}			0.04	

Significance Levels *** p<0.01, ** p<0.05, * p<0.1, significant coefficients are marked in bold

For H_1, the within coefficient on the time index is negative as predicted but statistically insignificant, reinforcing the conclusion that the data do not support a global monotonic improvement of *Forecast Accuracy* over time.

For H_3, the between coefficient on the segment-rank index is positive as predicted (631.53 EUR per rank step) and significant at the five percent level, indicating that, on average across the postulated ordering, each step toward a less important segment is associated with about 631 EUR of additional forecast error. Read in isolation, the linear-trend coefficient appears to support H_3. However, alongside the pairwise results in Table 35, it must be interpreted with care. The average linear trend masks the structured non-monotonicity in the data (Alpha being forecasted more accurately than Delta), and it is mechanically driven by the very large positive step between Alpha and Epsilon. The two specifications are therefore complementary. The linear-trend coefficient summarizes the average direction across the ordering, while the pairwise coefficients reveal which specific transitions drive that average and which contradict it. Taken together, the H_3 results support the multi-dimensional reading of *Segment Importance*. The volume ordering holds where sales volume co-moves with complexity and salience and breaks down where these dimensions diverge.

4.6 Discussion and Conclusion

This study investigated a highly relevant yet difficult to analyze field of research of accurate contribution margins forecasts during NPD. This field of research is of vivid interest as initial contribution margin forecasts determine project approvals and therefore the investment of huge sums by companies into their prospective product portfolio. Accordingly, exact project contribution margin forecasts are an essential driver for sustainable business success. Albeit such need to have exact forecasts, knowledge upon factors that influence its accuracy is limited as available data is scarce. Therefore, our analysis of proprietary archival data of an automotive OEM entitled us with a unique research opportunity that we used to investigate the impact of three potential determinants: *Time Effects*, *Production Effects*, and *Segment Importance*.

Regarding our first determinant of *Time Effects*, we expected an increase in accuracy as the project progress proceeds. Contrary to theory, development time is not a significant determinant in our dataset; only one time coefficient reaches significance, and only in the control specification. A plausible partial explanation is that ECC uses a stable forecasting approach across development stages and therefore does not harness the accuracy gains associated with more sophisticated, late-stage forecasting techniques (Qian and Ben-Arieh, 2008). However, we would have expected to see the postulated effect nonetheless as an increased data availability over time (Dahan and Hauser, 2002), reduced uncertainty over time (Voltolini et al., 2019), refinement and learning effects (Bajari et al., 2019) could have for themselves fostered the expected relationship. Rather, we interpret our findings as suggestion for our partner company to adapt its forecasting approaches. A future study in the industry context may investigate then precisely the impact of distinct forecasting techniques considering advancements over time (Qian and Ben-Arieh, 2008).

Concerning our second investigated determinant of *Production Effects*, the postulated hypothesis is clearly supported. The between effect – which captures the cross-sectional association between a project's production strategy and its *Forecast Accuracy* – is significant at the one percent level in our main as well as our control regression model. The significant between effect implies that inhouse-produced products are associated with significantly more accurate contribution margin forecasts than externally sourced ones. This finding aligns with the theoretical reasoning of Johnsen (2009) concerning the informational advantages of supply chain visibility for internally produced products. Besides, it aligns with the structured forecasting argument of Danese and

Kalchschmidt (2011). Practically, these findings suggest that cost experts at ECC possess better information about internally produced products, which is consistent with more accurate forecasts. Management-wise, our findings emphasize the importance of establishing tight information exchange with external suppliers to approximate the forecasting quality achievable for inhouse products. We note, however, that the between effect cannot establish causality – the association may also reflect that projects selected for inhouse production are inherently less complex or better understood, which would independently improve *Forecast Accuracy*.

Lastly, our third hypothesis concerned *Segment Importance*, which we operationalized through sales volume on the explicit premise that volume captures the dominant share of variation in management attention to forecast quality. The dummy specification in Table 34 already showed that segment Epsilon faces forecast errors 3,357.82 EUR higher than the reference Gamma, while segment Alpha shows significantly more accurate forecasts than the high-volume reference (-1,696.65 EUR). The pairwise adjacency tests in Table 35 sharpen the picture. The volume hypothesis holds at the low-volume end (Alpha to Epsilon, -5,054.48 EUR) and reverses at the small-car end (Delta to Alpha, 2,998.72 EUR). The linear-trend specification in Table 36 yields a positive between coefficient on the segment-rank index (631.53 EUR per rank step), indicating that *on average* across the postulated ordering each step toward a less important segment adds about 631 EUR of forecast error. The three specifications taken together support a multi-dimensional reading of *Segment Importance*: economic weight (volume) drives accuracy where it co-moves with complexity and salience but is dominated by complexity where the two diverge. We consider three potential mechanisms. First, *Alpha* products have inherently simpler architectures, fewer component variants, and a less complex bill of materials (Altavilla et al., 2018; Hammann, 2024; Niazi et al., 2006), which facilitates precise estimation. Second, they may be subject to fewer mid-development configuration changes, yielding a more stable forecasting basis. Third, experience effects may concentrate forecasting expertise in the smaller-car segment. The insignificance of *Beta* and *Delta*, meanwhile, suggests sales volume alone is insufficient as a proxy for forecasting attention.

The emerging picture is non-linear as both the volume-wise second smallest segment (*Alpha*, simple products and concentrated expertise) and the largest segments (*Gamma* and *Beta*, high strategic priority) achieve comparatively accurate forecasts, whereas the most exclusive and technically complex segment (*Epsilon*) lags. This shifts the explanatory focus from sales volume alone to the interplay of product complexity and strategic salience. Future research should operationalize *Segment Importance* via a composite measure combining economic relevance (e.g. sales volume times median net contribution margin) and inherent forecasting difficulty, disentangling management attention, product complexity, and forecasting expertise. Managerially, accurate forecasts underpin profound decision-making in the face of financial tradeoffs (Chwastyk and Kołosowski, 2014; Magnacca and Giannetti, 2024). Our direct recommendation is not to neglect complex niche segments. Senior management should actively pay more attention to these niche segments to create a sound information basis and eliminate a potential competitive disadvantage resulting from inefficient decision-making (Riedl et al., 2013; Wouters et al., 2009). Besides, sound contribution margin forecasts would also allow to efficiently assess the pressure and required effort to close the cost gap between allowable and realizable costs during product development by cost management activities (Ax et al., 2008; Ellram, 2002).

This paper added value to the scientific community as it provides insights into sensitive proprietary archival data of a leading automotive OEM analyzing its contribution margin forecasts. This dataset allowed us to investigate prominent predictors discussed in scientific contributions, i.e. *Time Effects*, *Production Effects*, and *Segment Importance* based on real industry data. Therefore, the given results add to the current state of knowledge of predictors concerning *Forecast Accuracy* (Disch, 2024).

Limitations of the dataset, i.e. no change in forecasting methods to account for the proclaimed impacts of *Time Effects* or the limited number of switches for our two other dummy variables, have been discussed. Another limitation concerns the generalizability of these findings as the unit of analysis are archival data of a single automotive company instead of a representative sample (Cooper and Slagmulder, 2004). Therefore, we reemphasize the impact of our study to be understood as single insight into practice that requires repeated analysis in similar setups before general conclusions could be made. Hence, we motivate to apply our research setup in other industrial companies, whenever accessibility and accepted agreement of usage apply. Besides, analyzing further determinants of *Forecast Accuracy* in an industrial setting may provide another research opportunity.

5 Conclusion

The purpose of this dissertation was to improve our understanding of financial tradeoffs during new product development (NPD) and the role of product architecture decisions, cost management methods, and forecast reliability of the contribution margin from NPD projects to address them. Competitive markets impose simultaneous demands on companies to deliver high-quality, differentiated products while maintaining cost levels that secure profitability. Decisions made during the early stages of NPD predetermine a large share of a product's total costs and create tradeoff situations that require decision-makers to prioritize among competing objectives. With a multi-method research design – comprising an integrative literature review, a method oriented study, and a proprietary archival study – we addressed financial tradeoffs from two complementary perspectives. The first perspective concerns the active management of financial tradeoffs, either by identifying how product architecture decisions affect these tradeoffs (Chapter 2) or by maximizing the achievable value within given cost constraints through a practically applicable extension of target costing based on cost-effectiveness (Chapter 3). The second perspective examines the reliability of the financial information on which these tradeoff management activities rely and thereby investigates the pressure to mitigate financial tradeoffs in the first place (Chapter 4). In this concluding chapter, we briefly summarize our main contributions, discuss limitations, and suggest future research opportunities.

In the integrative literature review (Chapter 2), we placed financial tradeoffs at the center of our analysis and answered two research questions: *"What financial tradeoffs arise around the development of new interdependent products?"* and *"What is the impact of product architecture decisions on these financial tradeoffs?"*. We contributed a conceptual framework that uses three distinct models, a financial tradeoff model based on the tradeoff framework of Wouters et al. (2016), an impact model of modular product design based on Salvador's (2007) five definitional perspectives, and an impact strength model. Building on and extending the tradeoff framework of Wouters et al. (2016) in the financial tradeoff model, we distinguished between tradeoffs concerning the unit economics of a single product and tradeoffs that arise from the interdependence between multiple products. There, overhead costs and NPD lead time connect the product level to the overarching project level. In the impact model of modular design, we systematically examined how product architecture decisions, particularly modularity, affect these tradeoffs through three groups of architecture impacts: variety management, manufacturing flexibility, and design options. Lastly, in the impact strength model, we illustrated that the choice of the modularization degree – common components, shared modules, joint platforms – affects the strength of the modularity impact. Besides, we also highlighted strategic benefits of modular product design through the economies of modularity and emphasized a research gap in management accounting leading to dysfunctional targets as local product-level optima are incentivized over a global project-level optimum. A critical assessment of the evidence base revealed a severe imbalance between analytical modeling and empirical financial validation across all identified tradeoffs. This finding is particularly consequential because it implies that decision-makers in practice are asked to make architecture choices that have long-lasting impacts on the basis of assumed rather than observed parameters. We found this imbalance to be consistent with empirical observations that architecture-related cost decisions are frequently made on intuition rather than financial analysis (Jørgensen and Messner, 2010, 2009).

In the extension of target costing (Chapter 3), we addressed a limitation of target costing: what to do when the cost gap between allowable and realizable product costs cannot be closed through conventional cost management activities such as value engineering or supplier development (Ax et al., 2008; Ellram, 2002). Developed through action research at our partner company European Car Corporation (ECC), we contributed a pragmatic, three-stage approach to identify the best realizable product within given financial boundaries. Starting from a predecessor product, the first stage creates a segment-specific minimum product by incorporating economies of learning, economies of efficiency, cost benchmarks, and legal requirements. The second stage enriches this product with mandatory components arising from commonality strategies. In the third stage, further technical product enrichment activities are selected based on cost-effectiveness – the additional property points relative to additional direct cost – until the allowable cost budget is fully exploited. We presented three optimization approaches (Approach A, B1, and B2) that differ in how they prioritize product properties and illustrated them with a fictional yet realistic numerical example. A key idea (guaranteed by the STEP restriction of the optimization) underlying this approach was the modeling of customer utility as a step function of discrete property levels rather than a continuous linear relationship: product improvements are found to be only significant when they reach the next recognizable level relative to competitor products. Besides, technical enrichment activities were required to be effective in addressing under fulfilled product properties (TARGET restriction of the optimization) while not exceeding the product level allowable cost (COST restriction of the optimization). This approach thereby overcomes several limitations of traditional target costing. Besides the already mentioned assumption of always closing the cost gap, the addressed limitations were the difficulty of breaking down product-level targets onto the component level for complex products (Ahn et al., 2018; Kajüter, 2013), neglected product interdependencies due to commonality strategies (Götze and Linke, 2008; Kee and Matherly, 2013; Ortelbach, 2005), and the assumption of a linear relationship between property improvements and customer responses (Goswami et al., 2017; Roy et al., 2008).

In the proprietary archival study on the forecast accuracy of the NPD project contribution margins (Chapter 4), we investigated potential determinants thereon based on proprietary archival data from ECC. Our dataset of 43 completed development projects provided us with a unique research opportunity as typically such information remains non-disclosed (Dierynck and Labro, 2018; Gallemore and Labro, 2015). Employing a correlated random effects regression approach, we analyzed the influence of three potential determinants: *Time Effects*, *Production Effects*, and *Segment Importance*. The dataset's richness – containing predicted actual, observed actual, planned target, and definite target values for the contribution margin – allowed us to operationalize forecast accuracy in a way that exploits the full complexity of real-world forecasting practices. We found that *Production Effects* significantly affect forecast accuracy, with inhouse-produced products exhibiting forecast errors that are on average 1,518.55 EUR lower than externally produced ones. This finding aligns with theoretical reasoning on supply chain visibility and structured forecasting processes (Danese and Kalchschmidt, 2011; Johnsen, 2009; Ragatz et al., 2002) and underscores the importance of establishing tight information exchange with external suppliers. Concerning *Segment Importance*, the results revealed a more nuanced pattern than the hypothesized monotonic relationship as the lowest-volume segment Epsilon exhibited significantly less accurate forecasts (by over 3,300 EUR per unit), while segment Alpha showed significantly more accurate forecasts. A linear-trend specification – mainly driven by the very large Alpha-to-Epsilon step – supports the volume hypothesis on average across the postulated ordering (about 631 EUR of additional forecast error per rank step). Together, these findings support a multi-dimensional reading of *Segment Importance* as it is influenced by several drivers besides sales volume. *Time Effects*, contrary to theoretical expectations, showed no significant influence in our dataset, which we attribute to ECC's use of a stable forecasting methodology throughout the development process that does not exploit more advanced techniques theoretically available at later stages.

This dissertation is subject to certain limitations related to the applied research methods. Whilst the study-specific limitations have been discussed in each of the three main chapters, we point out the main overarching limitations in the following paragraphs. The integrative literature review, while systematically covering diverse research streams, does not claim to present a fully exhaustive collection of all published evidence within the field. Due to the maturity and cross-disciplinary breadth of the underlying topics – product design, financial tradeoffs, cost management, and product development – some relevant contributions may not have been captured. However, we are confident that the review covers a significant and representative body of literature. The action research study and the proprietary archival study both draw on data and experiences from a single automotive company, ECC. In a single-case design, findings may underlie selective perceptions and subjective interpretations, and they are neither statistically generalizable nor automatically reproducible. Partnering closely with ECC meant also that we had limited control over the research setting, as practical challenges and requirements unfolded unpredictably over the three-year duration. However, we emphasize that this aspect also constitutes one of the most significant strengths of our research design as the longitudinal engagement at ECC generated detailed insights, research opportunities, and contributions that we could not have achieved through any other research approach. The numerical example in the target costing extension demonstrates the feasibility and internal logic of the approach rather than providing full empirical validation – a limitation inherent to the early-stage development of new methodological tools in applied settings. The proprietary archival study faces limitations concerning the dataset's unbalanced panel structure and the limited variability of certain independent variables over time, which we addressed through the correlated random effects approach and clustered standard errors.

The studies trigger several opportunities for future research. First, in Chapter 2 we identified an imbalance between analytical modeling of tradeoffs and their empirical validation. Future research could empirically calibrate the existing analytical models using actual cost data from companies that have implemented modular architectures, thereby closing the validation gap that our review identified as the most striking pattern across all tradeoffs. Therefore, our conceptual framework with its three models could be used as guiding theoretical setup for future investigations. Second, the target costing extension developed in Chapter 3 could be applied and tested in other industrial companies. Such studies could experiment with the approach's overall logic while adapting the specific considerations – cost benchmarks, learning and efficiency effects, commonality constraints, non-linear property improvements – to different organizational contexts. More broadly, future research could address product development situations in which strong cost pressure necessitates difficult tradeoffs between product properties given hard cost constraints, aiming to better understand how tradeoffs are being made and which methods are suitable under realistic conditions regarding data availability and unpredictability of customer preferences, competitor actions, and technological developments. Third, the findings from Chapter 4 motivate several avenues for further investigation. The non-significant *Time Effects* call for future studies that specifically analyze the impact of distinct forecasting techniques at different NPD stages using proprietary data, building on the methodological foundation established here. Our finding that *Segment Importance* follows a non-linear pattern rather than a monotonic sales-volume relationship suggests that future studies should operationalize *Segment Importance* alternatively to account for economic relevance and inherent forecasting difficulty. Furthermore, we encourage researchers to apply our research setup in other industrial companies whenever data access and usage agreements can be obtained, as repeated analysis in similar setups is needed before general conclusions can be drawn. Investigating further determinants of forecast accuracy in industrial settings may provide additional research opportunities.

In general, we found that management accounting literature tends to simplify the practical challenges and complexity of both financial tradeoffs and modular cost management during NPD. Conducting more studies that are inspired by real organizations' work could generate a more realistic understanding of how the mentioned cost management strategies operate in practice.

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7 Appendix

Appendix A: Literature Overview

Table 37 – Overview on the Most Cited Journals within this Literature Review

Journal Name	Total References	VHB-JOURQUAL3	SCImago
Journal of Product Innovation Management	11	A	Q1
IEEE Transactions on Engineering Management	8	B	Q1
International Journal of Production Economics	7	B	Q1
Management Science	7	A+	Q1
Journal of Engineering Design	6	not listed	Q2
International Journal of Operations & Production Management	5	B	Q1
Concurrent Engineering Research & Applications	3	not listed	Q2
European Journal of Operational Research	3	A	Q1
Journal of Intelligent Manufacturing	3	not listed	Q1
Manufacturing & Service Operations Management	3	A	Q1
Applied Sciences	2	not listed	Q3
Harvard Business Review	2	C	Q3
International Journal of Innovation and Technology Management	2	C	Q3
International Journal of Managing Projects in Business	2	not listed	Q2
International Journal of Production Research	2	B	Q1
Journal of Manufacturing Technology Management	2	k.R.	Q1
Journal of Mechanical Design	2	not listed	Q1
Marketing Science	2	A+	Q1
Production and Operations Management	2	A	Q1
Research Policy	2	A	Q1
Strategic Management Journal	2	A	Q1
Academy of Strategic Management Journal	1	not listed	not listed
Accounting Horizons	1	B	Q1
Accounting, Organizations and Society	1	A	Q1
Annual Reviews in Control	1	not listed	Q1
Artificial Intelligence for Engineering Design, Analysis and Manufacturing	1	not listed	Q2
Business Research	1	B	not listed
CIRP Annals	1	not listed	Q1
Cleaner Logistics and Supply Chain	1	not listed	Q1
Controlling	1	not listed	not listed
Engineering Costs and Production Economics	1	not listed	not listed
European Journal of Industrial Engineering	1	not listed	Q2
European Journal of Marketing	1	C	Q1
Innovation	1	not listed	Q1
International Journal of Automotive Technology and Management	1	C	Q2
International Journal of Flexible Manufacturing Systems	1	B	Q1
International Journal of Industrial and Systems Engineering	1	not listed	Q3
International Journal of Management Reviews	1	not listed	Q1
International Journal of Strategic Cost Management	1	not listed	not listed
Journal of Engineering and Technology Management	1	C	Q1
Journal of Intelligent & Fuzzy Systems	1	not listed	Q2
Journal of Management Accounting Research	1	B	Q2
Journal of Management and Governance	1	C	Q1
Journal of Marketing	1	A+	Q1
Pricing Strategy and Practice	1	not listed	not listed
Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture	1	not listed	Q2
Production Engineering	1	not listed	Q2
Production Engineering – Research and Development	1	not listed	Q2
Qualitative Research in Accounting & Management	1	B	Q2
Research in Engineering Design	1	not listed	Q1
SAE Transactions	1	not listed	not listed
Sloan Management Review	1	C	Q2
Strategy & Leadership	1	C	Q3

Systems Engineering	1	not listed	Q2
Technovation	1	C	Q1
The International Journal of Advanced Manufacturing Technology	1	not listed	Q2
Total Quality Management & Business Excellence	1	not listed	Q1

Appendix B: Further Tradeoff Models during NPD

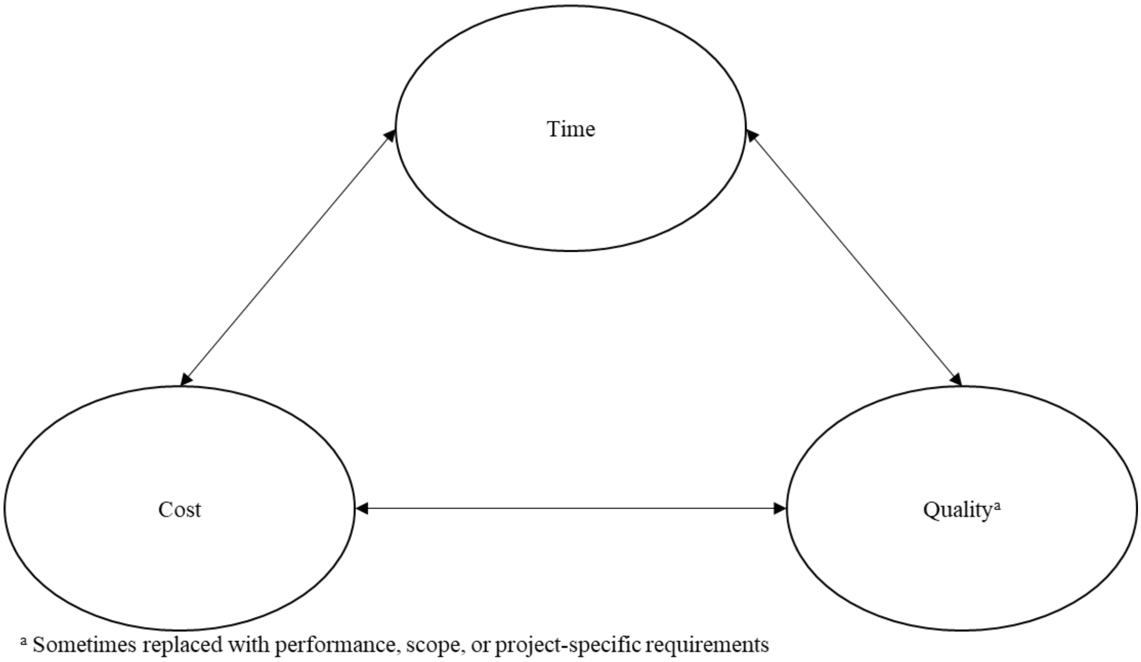

Figure 28 – Iron Triangle of Project Management, copied from Pollack et al. (2018, p. 532)

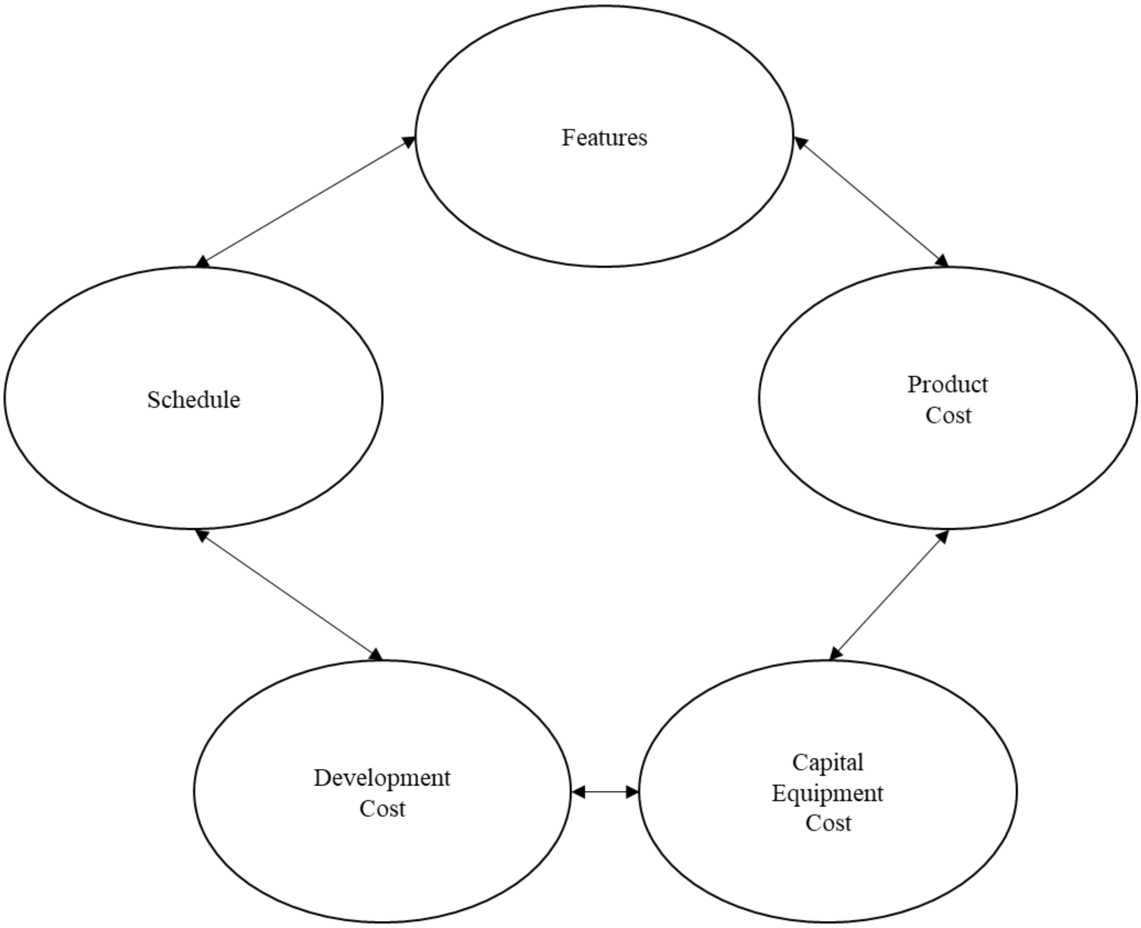

Figure 29 – Tradeoff Model, copied from Rose (2013)

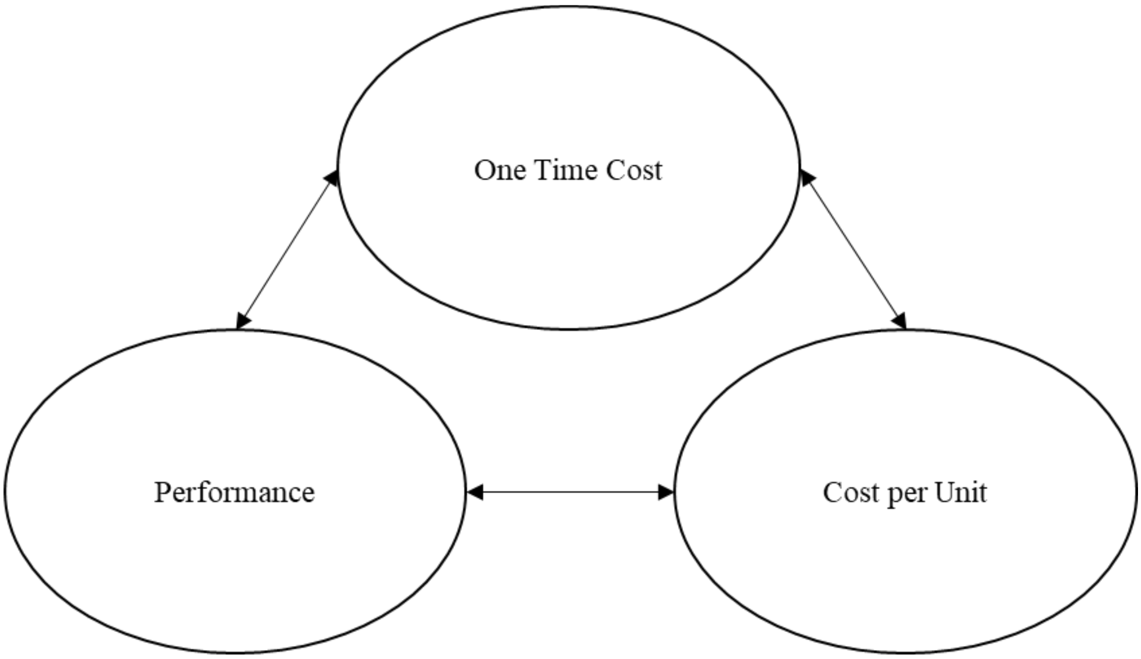

Figure 30 – Tradeoff Model, copied from Bakker et al. (2020, pp. 6–7)