Cooperative R&D Projects between Biotechnology Firms and Public Research Institutes: Determinants of Success from a Product Competitive Advantage Perspective

von

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Abstract

While the existing literature on cooperative R&D projects between firms and public research institutes (PRI) has made valuable contributions by examining various factors and their influence on different outcome measures, there has been no investigation of cooperative R&D project success between firms and PRI from a product competitive advantage perspective. However, insights into the development of a meaningful and superior product (i.e., product competitive advantage) are particularly important in the context of cooperative R&D projects between PRI and (mainly small and medium-sized) firms in the biotechnology industry in response to increasing competition to raise capital funds necessary for survival.

The objectives of this thesis are: (1) to elaborate the theoretical foundations which explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI, (2) to identify and empirically evaluate the determining factors for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI, and (3) to show how cooperative R&D projects between biotechnology firms and PRI should be designed and executed to support the achievement of a product competitive advantage.

To accomplish these objectives, a model of determinants of product competitive advantage in cooperative R&D projects between biotechnology firms and PRI is developed by drawing from the theoretical foundations of resource-based theory and information-processing theory. The model is evaluated using data from 517 questionnaires on cooperative R&D projects between at least one biotechnology firm and one PRI. The data are analyzed using variance-based structural equation modeling (i.e., PLS-SEM) in order to conduct hypotheses testing. The evaluation of the empirical data includes an additional mediation analysis and the comparison of effects in subsamples.

The results demonstrate the importance of available resources and skills, as well as the proficient execution of marketing-related and technical activities for the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. By identifying project-related and process-related factors affecting product competitive advantage and empirically testing their relationships, the research findings should be valuable for both researchers and practitioners. After discussing contributions and implications for research and practice, the present thesis concludes with limitations and avenues for future research.

Zusammenfassung

Während die bestehende Literatur zu kooperativen F&E-Projekten zwischen Unternehmen und öffentlichen Forschungseinrichtungen mit der Untersuchung verschiedener Faktoren und deren Einfluss auf bestimmte Erfolgsmaße bereits einen wertvollen Beitrag geleistet hat, ist der Erfolg dieser kooperativen Vorhaben bislang noch nicht aus der Perspektive eines Produktwettbewerbsvorteils beleuchtet worden. Erkenntnisse über die Entwicklung eines für Nutzer bedeutungsvollen und der Konkurrenz überlegenen Produktes (d.h. die Erzielung eines Produktwettbewerbsvorteils) sind allerdings von besonderer Bedeutung im Kontext von kooperativen F&E-Projekten zwischen öffentlichen Forschungseinrichtungen und den primär kleinen und mittelständischen Unternehmen in der Biotechnologieindustrie, um im zunehmenden Wettbewerb überlebensnotwendiges Kapital einwerben zu können.

Die Ziele dieser Arbeit sind: (1) die theoretischen Grundlagen zu erarbeiten, die das Erreichen eines Produktwettbewerbsvorteils in kooperativen F&E-Projekten zwischen Biotechnologieunternehmen und öffentlichen Forschungseinrichtungen erklären, (2) die Einflussfaktoren bei der Erzielung eines Produktwettbewerbsvorteils in kooperativen F&E-Projekten zwischen Biotechnologieunternehmen und öffentlichen Forschungseinrichtungen zu identifizieren und empirisch zu prüfen und (3) aufzuzeigen, wie kooperative F&E-Projekte zwischen Biotechnologieunternehmen und öffentlichen Forschungseinrichtungen gestaltet und durchgeführt werden sollten, um die Erzielung eines Produktwettbewerbsvorteils zu unterstützen.

Um diese Ziele zu erreichen, wird ein Modell der Einflussfaktoren des Produktwettbewerbsvorteils in kooperativen F&E-Projekten zwischen Biotechnologieunternehmen und öffentlichen Forschungseinrichtungen entwickelt, das auf den theoretischen Grundlagen der ressourcenbasierten Theorie und der Theorie der Informationsverarbeitung aufbaut. Das Modell wird anhand von Daten aus 517 Fragebögen zu kooperativen F&E-Projekten zwischen mindestens einem Biotechnologieunternehmen und einer öffentlichen Forschungseinrichtung evaluiert. Die Daten werden mit Hilfe der varianzbasierten Strukturgleichungsmodellierung (PLS-SGM) analysiert, um Hypothesentests durchzuführen. Die Auswertung der empirischen Daten beinhaltet eine zusätzliche Mediationsanalyse sowie eine Multigruppenanalyse.

Die Ergebnisse verdeutlichen die Bedeutung von vorhandenen Ressourcen und Fähigkeiten sowie der fachkundigen Durchführung von marketingbezogenen und technischen Aktivitäten bei der Erzielung eines Produktwettbewerbsvorteils in kooperativen F&E-Projekten zwischen Biotechnologieunternehmen und öffentlichen Forschungseinrichtungen. Durch die Identifizierung von projekt- und prozessbezogenen Einflussfaktoren des Produktwettbewerbsvorteils sowie die empirische Überprüfung ihrer Beziehungen sollten die Forschungsergebnisse sowohl für Forscher als auch für Praktiker von Nutzen sein. Nach der Diskussion der Beiträge und Implikationen für Forschung und Praxis schließt die vorliegende Dissertation mit der Darstellung von möglichen Limitationen der Forschungsstudie und Ansatzpunkten für die zukünftige Forschung.

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List of Abbreviations

AVE	average variance extracted
CB-SEM	covariance-based structural equation modeling
e.g.	exempli gratia (for example)
HHM	human health and medicine
HTMT ratio	heterotrait-monotrait ratio
i.e.	id est (that is)
f.	following
ff.	and the following ones
MICOM	measurement invariance of composite models procedure
n.s.	not significant
NPD	new product development
p.	page
PLS-SEM	partial least squares structural equation modeling
PRI	public research institutes
R&D	research and development
VIF	variance inflation factor

1 Introduction

1.1 Motivation

1.1.1 Relevance of the Topic

The growing sophistication of leading-edge technologies has dramatically increased the importance of cooperative research and development (R&D) between firms and public research institutes (PRI)[1] (Ahn 1995, p. 242; Mora-Valentin et al. 2004, p. 17; Ortiz 2013, p. 281). In science-based industries – especially in the biotechnology industry – small and medium-sized firms need to cooperate in R&D with PRI in order to cope with their heavy reliance on scientific expertise (Ortiz 2013, p. 281ff.). Due to the complexity and interdisciplinarity of biotechnology, it is not possible for a single organization to internally unite all the necessary resources and skills (i.e., specialized knowledge) to competently execute the multitude of tasks of biotechnology R&D, which is characterized by various and highly specialized techniques (e.g., protein synthesis; OECD 2005, p. 7 ff.). Consequently, cooperative R&D projects between biotechnology firms and PRI are initiated to gain access to specialized knowledge that is needed to perform the tasks of R&D (Ortiz 2013, p. 281). Such cooperative R&D projects are to be regarded as temporary forms of organization in which the partners' complementary resources and skills are combined with the objective to create new knowledge that can be patented and/or results in a prototype (Rothaermel/Deeds 2004, p. 204; Ortiz 2013, p. 281 f.). The anticipated outcome of cooperative R&D projects between biotechnology firms and PRI is a product (i.e., a biotechnological invention[2]), which has the potential to raise money for the subsequent costly and time consuming (clinical) testing efforts until a biotechnological invention results in a marketable product (e.g., pharmaceutical drug) (Rothaermel/Deeds 2004, p. 204; Schüler 2016, p. 167ff.).

[1] A public research institute is a division of a public research organization - university or non-university research organization (e.g., Max-Planck Society) - that is devoted to a particular scientific discipline (e.g., biotechnology).

[2] ""Biotechnological inventions" are inventions which concern a product consisting of or containing biological material or a process by means of which biological material is produced, processed or used" (The European Patent Convention, R. 26 (2)).

However and in contrast to a decade ago, it now requires more than just promising research results to attract investors (Ernst & Young 2013, p. 31[3]). The German biotechnology industry has grown out of its "infancy" with the consequence of increasing competition alongside limited private investments.[4] To attract investors and thus to survive in this industry, a product (i.e., a biotechnological invention) is needed that offers unique performance characteristics and is superior in quality as well as in meeting the needs of a target audience (e.g., potential investors) (Ernst & Young 2013, p. 31[5]; Ernst & Young 2014, p. 11[6]). Literature on new product development (NPD) terms such a product's perceived superiority relative to competitors' offerings a product competitive advantage (Song/Parry 1999, p. 673).

In conclusion, success of cooperative R&D projects between biotechnology firms and PRI is linked to the resulting product (i.e., a biotechnological invention) and its superiority to competitive offerings (i.e., product competitive advantage) in order to gain access to financial capital that is needed for subsequent testing efforts until a biotechnological invention results in a marketable product (e.g., pharmaceutical drug).

1.1.2 Research Problem and Questions

Despite a considerable amount of studies, extant research on R&D cooperations has not yet - neither theoretically nor empirically - addressed the question of what are the determining factors for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. Extant literature on R&D cooperations between firms and PRI has extensively focused on investigating the determinants of cooperation ("why to cooperate") as well as the

[3] Reference based on an article written by Dr. Jörg Fregien, CEO Life Science Inkubator, Bonn.

[4] An excellent discussion on the lack of private investments (e.g., through initial public offerings and/or venture capital) in the German biotechnology is provided by Schüler (2016, p. 343 ff.).

[5] See footnote no. 2.

[6] Reference based on an article written by Dr. Karsten Henco. Dr. Henco is co-founder or co-founding investor of several biotechnology companies in Germany, USA, Canada and Austria such as Qiagen NV, Evotec AG, NewLab AG, Coley Pharmaceuticals Inc, U3 Pharma AG, Neurimmune Therapeutics AG, Zurich, Switzerland, Medesso GmbH, CT Atlantic AG, HS LifeSciences, AG and QureInvest II SICAR and its portfolio companies.

respective partner selection ("with whom"; e.g., Miotti/Sachwald 2003; Arranz/de Arroyabe 2008; Barge-Gil 2010; Cassiman et al. 2010; de Faria et al. 2010; Arza/López 2011; Okamuro et al. 2011; Chun/Mun 2012). Another part of research examined the impact of R&D cooperations on different output measures (e.g., Miotti/Sachwald 2003; Faems et al. 2005; Schwartz et al. 2012), and some authors are concerned with the relationship between characteristics of cooperative R&D projects (e.g., geographic proximity between partners) and project success (e.g., Mora-Valentin et al. 2004; Petruzzelli 2011; Schwartz et al. 2012).

Investigating the determinants for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI is an interesting but not yet addressed research problem. According to Alvesson/Kärreman (2007, p. 1268), an interesting or valuable research problem includes a novel understanding or perspective to previous research. Studying success of cooperative R&D projects between firms and PRI from the perspective of product competitive advantage is supposed to provide such a novel understanding. Knowledge about the determining factors for achieving a product competitive advantage is of special interest, since it offers insights into how to manage cooperative R&D projects between biotechnology firms and PRI in order to develop a superior and unique product. Such insights not only serve the purpose of theory advancement in the domain of R&D cooperations between firms and PRI but also serve the needs of practitioners by guiding the management of such arrangements. In particular, the following research questions need to be addressed:

- What are the theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?
- What are the project-related and process-related factors affecting product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?
- How are these determinants interrelated and in which ways do they contribute to the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?

This thesis aims to answer these questions. By drawing from theoretical foundations of resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978), as well as research on NPD, a conceptual model will be developed and empirically tested. This thesis is supposed to contribute to the existing literature on R&D cooperations by - for the first time - conducting research on success of cooperative R&D projects between biotechnology firms and PRI from the perspective of achieving a product competitive advantage. The central contribution is to conceptually link success of cooperative R&D projects between firms and PRI to achieving a product competitive advantage, which is essential to attract investors and thus to survive in the biotechnology industry (Ernst & Young 2013, p. 31[7]; Ernst & Young 2014, p. 11[8]). By identifying project-related and process-related factors affecting product competitive advantage and empirically testing their relationships, the implications of the results should be interesting to both academicians and practitioners. In particular, the findings may be of considerable value and interest to executives faced with the complex task of managing cooperative R&D projects between biotechnology firms and PRI.

This research venture continues with a discussion on state-of-the-art-research on R&D cooperations in Section 1.2. In particular, the extant literature on R&D cooperations between firms and PRI is reviewed to provide an overview of existing research. Building on this review, the purpose of Section 1.3 is to clarify the identified research needs. The objectives of the doctoral thesis are formulated in Section 1.4. In Section 1.5, the research design is presented. Further in Section 1.6, the structure of this dissertation is illustrated.

1.2 State-of-the-Art-Research: R&D Cooperations between Firms and PRI

R&D cooperations[9] are "formal collaborative arrangements among organizations with the objective to co-operate on research and development activities"

[7] See footnote no. 2.

[8] See footnote no. 5.

[9] The terms "cooperation" and "collaboration" are used interchangeably throughout literature. For simplification reasons, I will further refer to the term "R&D cooperation".

(Petruzzelli 2011, p. 310). Literature on R&D cooperations between PRI and firms features a considerable amount of studies concerned with the determinants of cooperation ("why to cooperate") as well as the respective partner selection ("with whom"; Schwartz et al. 2012, p. 358; e.g., Miotti/Sachwald 2003; Arranz/de Arroyabe 2008; Barge-Gil 2010; Cassiman et al. 2010; de Faria et al. 2010; Arza/López 2011; Okamuro et al. 2011; Chun/Mun 2012). Empirical research conducted by Miotti/Sachwald (2003) found that firms which permanently conduct R&D activities seek R&D cooperations with PRI. Those cooperative R&D activities with PRI are most attractive to firms that rely on scientific resources to innovate (Miotti/Sachwald 2003, p. 1489 ff.). PRI are regarded as useful suppliers of basic and specialist knowledge, especially in emerging technologies (Tether 2002, p. 953). Consequently, they are more likely to partner in R&D cooperations that involve new and more uncertain technological fields (Hall et al. 2003, p. 491).

In addition, some authors study the impact of R&D cooperation of firms with PRI on different output or performance measures (Schwartz et al. 2012, p. 358). For example, Miotti/Sachwald (2003, p. 1493 f.) found that patenting is positively influenced by cooperation with PRI. Other performance measures include a firm's proportion of turnover generated by technologically new products (e.g., Faems et al. 2005), or the number of publications (e.g. Schwartz et al. 2012).

Another stream of research focuses on factors that determine the success of R&D cooperations between firms and PRI (see Tables 1 to 4). Petruzzelli (2011) examined the link of technological relatedness, prior collaboration ties, and geographical distance between the partners and success of the cooperation. Adopting the R&D cooperation project between firms and PRI as the unit of analysis, Schwartz et al. (2012) similarly studied the relationship between project success and the partners' cooperation experience as well as their spatial proximity. In an extensive field study, Mora-Valentin et al. (2004) investigated the determining organizational and contextual factors of the success of 800 cooperative R&D projects between firms and PRI in Spain. The factors under investigation included those factors that are prominently discussed in the literature on inter- and intra-firm knowledge transfer (e.g., Szulanski 1996; Simonin 1999a, 1999b).

Though studies in the latter stream greatly contribute to the understanding of the influence of cooperative R&D project characteristics and factors related to knowledge transfer on different measures of success, the extant literature has not yet investigated cooperative R&D project success between firms and PRI from a product competitive advantage perspective. The following sections discuss this need in research on R&D cooperations between firms and PRI and formulate the objectives of this thesis.

Table 1: Studies focusing on factors that determine the success of R&D cooperations between firms and PRI (I)

Study	Empirical Setting	Method	Operationalization of Success	Empirical Results
Mora-Valentin et al. (2004) (I)	Field study of 800 cooperative agreements between Spanish firms and research organizations.	Structural equation model	Two indicators of success: Global satisfaction of the partners of the agreement and the evolution of the relationship. Global satisfaction was measured by five items referring to specific global aspects of the project such as the partner's performance, the development of the agreement and the global results of the project. Evolution of the relationship referred to five items that describe the different situations that may occur in the development of the agreement.	Previous cooperative experiences had a positive influence only on the evolution of the relationship between firms and research organizations. Partners' good reputation had a positive influence only on the satisfaction of cooperative agreements between firms and research organizations in the sample of research organizations. A clear definition of objectives had a positive influence only on the satisfaction of cooperative agreements between firms and research organizations in the sample of firms. A higher degree of institutionalization had no significant influence on the success of cooperative agreements between firms and research organizations.

Table 2: Studies focusing on factors that determine the success of R&D cooperations between firms and PRI (II)

Study	Empirical Setting	Method	Operationalization of Success	Empirical Results
Mora-Valentin et al. (2004) (II)	Field study of 800 cooperative agreements between Spanish firms and research organizations.	Structural equation model	Two indicators of success: Global satisfaction of the partners of the agreement and the evolution of the relationship. Global satisfaction was measured by five items referring to specific global aspects of the project such as the partner's performance, the development of the agreement and the global results of the project. Evolution of the relationship referred to five items that describe the different situations that may occur in the development of the agreement.	Greater geographic proximity between partners had no significant influence on the success of cooperative agreements between firms and research organizations. More commitment had a positive influence on the success of cooperative agreements between firms and research organizations. Better communication had a positive influence only on the satisfaction of cooperative agreements between firms and research organizations in the sample of research organizations. Higher levels of trust had a positive influence only on the evolution of the relationship between firms and research organizations in the sample of research organizations.

Table 3: Studies focusing on factors that determine the success of R&D cooperations between firms and PRI (III)

Study	Empirical Setting	Method	Operationalization of Success	Empirical Results
Mora-Valentin et al. (2004) (III)	Field study of 800 cooperative agreements between Spanish firms and research organizations.	Structural equation model	Two indicators of success: Global satisfaction of the partners of the agreement and the evolution of the relationship. Global satisfaction was measured by five items referring to specific global aspects of the project such as the partner's performance, the development of the agreement and the global results of the project. Evolution of the relationship referred to five items that describe the different situations that may occur in the development of the agreement.	A higher level of conflict had a negative influence on the success of cooperative agreements between firms and research organizations in the sample of firms. Greater dependence among partners had no significant influence on the success of cooperative agreements between firms and research organizations.

Table 4: Studies focusing on factors that determine the success of R&D cooperations between firms and PRI (IV)

Study	Empirical Setting	Method	Operationalization of Success	Empirical Results
Petruzzelli (2011)	796 university-industry joint patents, developed by 33 universities located in 12 different European countries.	Negative binominal regression	Value of joint innovations: Number of citations received by each university-firm joint patent.	Technological relatedness between universities and firms had an inverted U-shaped relationship with the value of joint innovations. Prior collaboration ties between universities and firms had a positive effect on the value of joint innovations. No significant negative effect of geographical distance between universities and firms on the value of joint innovations.
Schwartz et al. (2012)	313 R&D cooperation projects between firms and public research institutes in Germany.	Negative binominal regression	Number of patents and publications that directly emerged from an R&D project.	No significant relationship between the spatial proximity between partners and number of patents/publications. No significant relationship between partners' prior cooperation experience and number of patents/publications.

1.3 Research Needs

Cooperative R&D projects are born with the aim of achieving specific objectives, and success of such a project is determined by the achievement of the pursued objectives (Mora-Valentin et al. 2004, p. 18). In cooperative R&D projects between biotechnology firms and PRI, the objective or anticipated outcome is a product (i.e., a biotechnological invention; Rothaermel/Deeds 2004, p. 204) that is superior to competitive offerings (i.e., product competitive advantage) (Ernst & Young 2013, p. 31; Ernst & Young 2014, p. 11). Thus, the assessment of product competitive advantage is basic in order to know to what extent the defined objective in cooperative R&D projects between biotechnology firms and PRI have been attained. Under the premise that projects must be planned and executed with its objectives in mind (Shenhar et al. 2001, p. 713f.), it is of special interest in the context of cooperative R&D projects between biotechnology firms and PRI which project-related (e.g., complementary resources and skills) and process-related variables (e.g., conducting market research) are beneficial for achieving a product competitive advantage. However, the determining factors for achieving a product competitive advantage in such arrangements have not yet been examined. Knowledge about the determining factors for achieving a product competitive advantage may be of special interest to executives, since it provides insights into how to manage cooperative R&D projects between biotechnology firms and PRI in order to develop a superior and unique product. In addition, such an examination would contribute to the extant literature by adopting a novel perspective (i.e., the perspective of product competitive advantage) in the discussion on success of joint R&D projects between firms and PRI.

Based on the review of existing empirical research on R&D cooperations between firms and PRI (see Section 2) and the above-illustrated importance of studying the determinants of product competitive advantage in cooperative R&D projects between biotechnology firms and PRI, the following research needs can be identified:

(1) The underlying theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI have not been investigated so far.

(2) The determining factors for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI have not been identified and tested (i.e., quantitative, hypotheses testing) in an empirical setting.

1.4 Research Objectives

This section presents the research objectives that are central to this dissertation. These objectives are derived from the aforementioned research needs. The overall objective is to identify and empirically test the determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. This study is intended to provide the necessary theoretical basis and empirical evidence to carry out an in-depth analysis of the determining factors for achieving a product competitive advantage in such arrangements. By drawing from theoretical foundations of resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978), as well as research on NPD, a conceptual model will be developed and empirically tested. This thesis is supposed to contribute to existing literature on this topic by conducting research on success of cooperative R&D projects between biotechnology firms and PRI from the perspective of achieving a product competitive advantage for the first time.

In sum, the subject of this thesis will be the following three research objectives:

- Research objective 1: This dissertation strives to elaborate the theoretical foundations which explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI.
- Research objective 2: This dissertation aims to identify and quantitatively test the determining factors for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI by using structural equation modeling. This approach allows capturing the interrelationships among determinants as well as assessing in which ways they contribute to achieving a product competitive advantage.

- Research objective 3: This dissertation intends to show how cooperative R&D projects between biotechnology firms and PRI should be designed and executed to support the achievement of a product competitive advantage.

The next section presents the research design of this thesis.

1.5 Research Design

The research design of any thesis is supposed to answer the questions of what methodologies and methods are used and how their employment is justified (Crotty 1998, p. 2). This is done in this section by following Crotty's (1998) four basic elements of the research process, that is, epistemology, theoretical perspective, methodology, and method (see Figure 1).

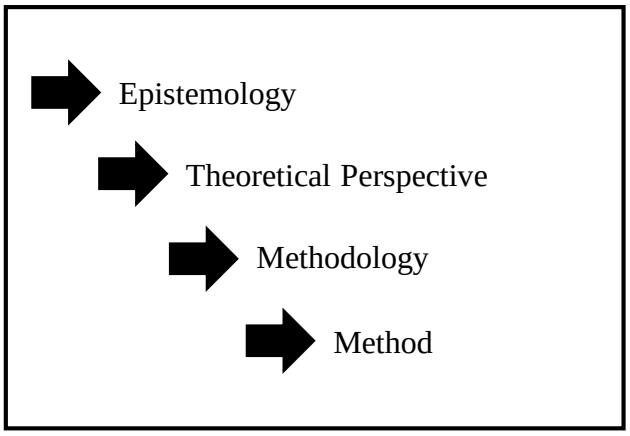

Figure 1: Four basic elements of the research process[10]

According to Hughes/Sharrock (2016, p. 11), every scientific investigation and its techniques and methods employed require epistemological justification. Epistemology is "the theory of knowledge embedded within the theoretical perspective and thereby in the methodology" (Crotty 1998, p. 3). This theory of knowledge focuses on the questions about how knowledge is created and what man can actually know (Moon/Blackman 2014, p. 4). For instance, epistemology is concerned with whether knowledge exists independently of the individual, thus can be identified by research in an objective way, or whether knowledge is bound to humans, thus being subjective by nature (Moon/Blackman 2014, p. 5). The

[10] Figure adapted from Crotty (1998, p. 5).

epistemological perspective that represents a researcher's conviction with respect to knowledge and its discovery influences his or her choice regarding methodology and methods applied in order to illuminate the research problem of interest (Moon/Blackman 2014, p. 5).

This thesis is influenced by the convictions of objectivist epistemology. Objectivist epistemology argues that there is a reality that exists independently of the individual (human) consciousness (Crotty 1998, p. 9; Moon/Blackman 2014, p. 5), and that knowledge and truth is contained in the world separately from people's experience of it (Bellefeuille 2006, p. 86). Objectivist epistemologists assume that an objective truth can be discovered by science (Crotty 1998, p. 9). This objective truth is "empirically verifiable, valid, generalizable, and independent of social thought and social conditions […]" (Moon/Blackman 2014, p. 5). Therefore, objective epistemology suggests that scholars can "rationally come to know the world as it really is; the facts of the world are essentially there for study" (Pratt 1998, p. 23; cited in Moon/Blackman 2014, p. 5)."

The theoretical perspective refers to a kind of value system to which the researcher relates to (Crotty 1998, p. 3; Moon/Blackman 2014, p. 7), a set of assumptions or a "basic set of beliefs" (Guba 1990, p. 17) that drives the way research is conducted (Moon/Blackman 2014, p. 7). The theoretical perspective of research ventures must be made explicit, since the theoretical perspective of research projects contains assumptions that significantly influence the research design (i.e. the choice of methodology and method) (Crotty 1998, p. 8f.; Moon/Blackman 2014, p. 7). This thesis is based on the theoretical perspective of positivism. Positivism is closely linked to objectivist epistemology and is based on the conviction that „only knowledge gained through the scientific method through unprejudiced use of the senses is accurate and true" (Moon/Blackman 2014, p. 7). The positivist mode of inquiry assumes that an objective reality exists. Its purpose is generalisability, prediction and/or causal explanations. The positivist school follows a deductive approach (i.e., developing hypotheses based on theory, and then testing them), uses formal, structured instruments and reduces data to numerical indices (Yilmaz 2013, p. 314).

The theoretical perspective has a decisive influence on the methodology (Crotty 1998, p. 3). Methodology is "the strategy, plan of action, process or design lying behind the choice and use of particular methods and linking the choice and use of methods to the desired outcomes" (Crotty 1998, p. 3). The methodology used in this thesis was survey research, since this quantitative research approach corresponds with the beliefs of positivism (Yilmaz 2013, p. 312). Positivism is characterized by the use of operational definitions, objectivity, replicability and causality (Bryman 1984, p. 77). In the tradition of positivism, the survey is the preferred tool, as it can be adapted to these characteristics. Concepts or variables are operationalized through questionnaire items. The use of a standardized questionnaire ensures a certain level of objectivity. Replication is possible by applying the same research instrument (i.e., the same or slightly adapted questionnaire) in another research context. Finally, questionnaires are well suited to collect data for the purpose of causality analyses through the use of structural equation modeling (Bryman 1984, p. 77). Consequently, the method of this thesis (i.e., the technique or procedure applied in order to gather data with respect to the research objective; Crotty 1998, p. 3) is the questionnaire. The research design of this thesis is summarized in Figure 2.

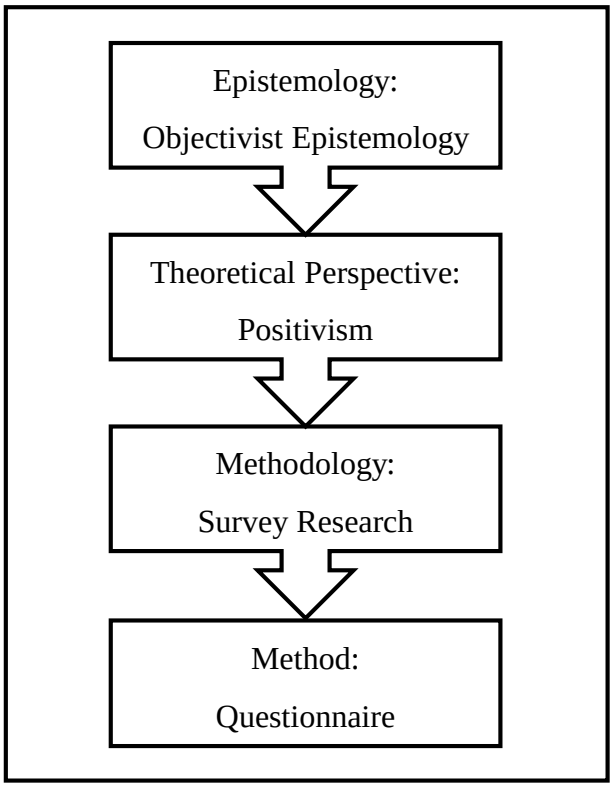

Figure 2: Research design of the thesis[11]

1.6 Structure

The first section, "Introduction", began by presenting the topic by illustrating the relevance of achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. Subsequently, the research problem and questions were described, followed by presenting state-of-the-art-research on R&D cooperations between firms and PRI. In addition, the corresponding research needs, the research objective, and the research design of this dissertation were discussed. This subsection introduces the structure of the thesis.

To develop a conceptual model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective, the second section discusses the "Conceptual Principles". With respect to the conceptual principles of product competitive advantage, the link between superior and meaningful products with successful NPD projects is discussed (Section 2.1.1). In addition, the role of project-related factors (i.e., fit of

[11] Figure adapted from Crotty (1998, p. 4).

available resources and skills with the project requirements; Section 2.1.2) and process-related factors (i.e., the proficient execution of NPD activities; Section 2.1.3) for obtaining a product competitive advantage are illustrated. After this presentation of the conceptualization of product competitive advantage in the extant literature on NPD, the characteristics of the biotechnology industry are depicted (Section 2.2.1). To conclude the second section, state-of-the-art-research on R&D cooperations in the biotechnology industry are summarized (Section 2.2.2).

In the third section, "A Model of Determinants of Success from a Product Competitive Advantage Perspective" in the context of cooperative R&D projects between biotechnology firms and PRI is developed. This section is divided into three parts. First, the underlying theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI are presented (Section 3.1). These theoretical foundations involve resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978). Second, the conceptual model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective is developed (Section 3.2). Third, the hypotheses of this thesis are formulated with regard to the research model (Section 3.3).

The objective of the analysis in the fourth section, "Empirical Analysis of the Research Model", is to evaluate the model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. In order to conduct the empirical analysis of the research model, the first step involves defining the cooperative R&D project between a biotechnology firm and a PRI as the object of study (Section 4.1). The second step involves the description of the process of data collection (Section 4.2). Hypotheses testing is conducted by means of the quantitative research methodology of a survey, allowing the factors of the research model to be systematically captured. Therefore, the third step involves the operationalization of the variables (Section 4.3). The fourth and fifth step involves the presentation of the questionnaire (Section 4.4) and the description of the sample (Section 4.5), respectively. The sixth step involves the descriptive analysis concerning the

variables of the research model (Section 4.6) and the seventh step involves introducing structural equation modeling as a means of measuring the hypothesized relationships of the research model (Section 4.7). The final step involves analyzing the gathered data, and the results are discussed an analyzed (Section 4.8).

Section “Summary, Conclusion, and Outlook” concludes the thesis with an overview of the findings, theoretical contributions and implications, practical implications, as well as limitations and avenues for future research. Section 5.1 begins with an overall summary of the thesis. Section 5.2 addresses the contributions and implications for theory. Section 5.3 addresses practical implications with respect to the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. Finally, Section 5.4 discusses the limitations of the study and further research needs.

Figure 3 summarizes the structure and course of investigation of the thesis.

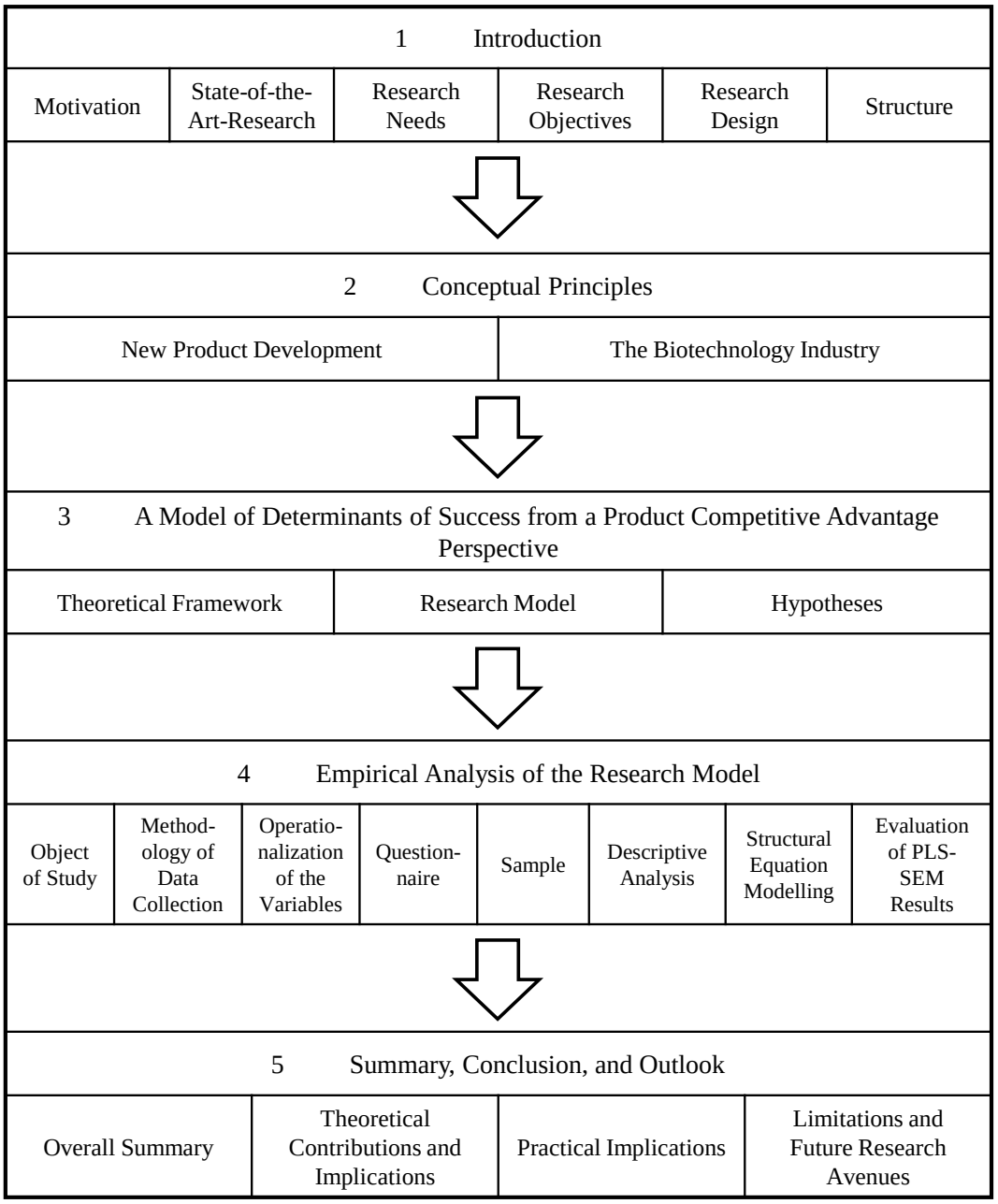

Figure 3: Structure of this thesis

2 Conceptual Principles

With regard to the conceptual principles of product competitive advantage, Section 2.1.1 demonstrates the close association of product competitive advantage with successful NPD ventures. Next, the role of project-related variables (i.e., fit of available resources and skills with the project requirements; Section 2.1.2) and process-related factors (i.e., the proficient execution of NPD activities; Section 2.1.3) in achieving a product competitive advantage is illustrated.

After having depicted the conceptualization of product competitive advantage in the extant literature on NPD, Section 2.2.1 serves as an introduction to the characteristics of the biotechnology industry. Finally, Section 2.2.2 synthesizes state-of-the-art-research on R&D cooperations in the biotechnology industry.

2.1 New Product Development

2.1.1 Product Competitive Advantage

Product competitive advantage is a theoretical construct that is composed of two components: product superiority and product meaningfulness (Rijsdijk et al. 2011, p. 33ff.) (see Figure 4).

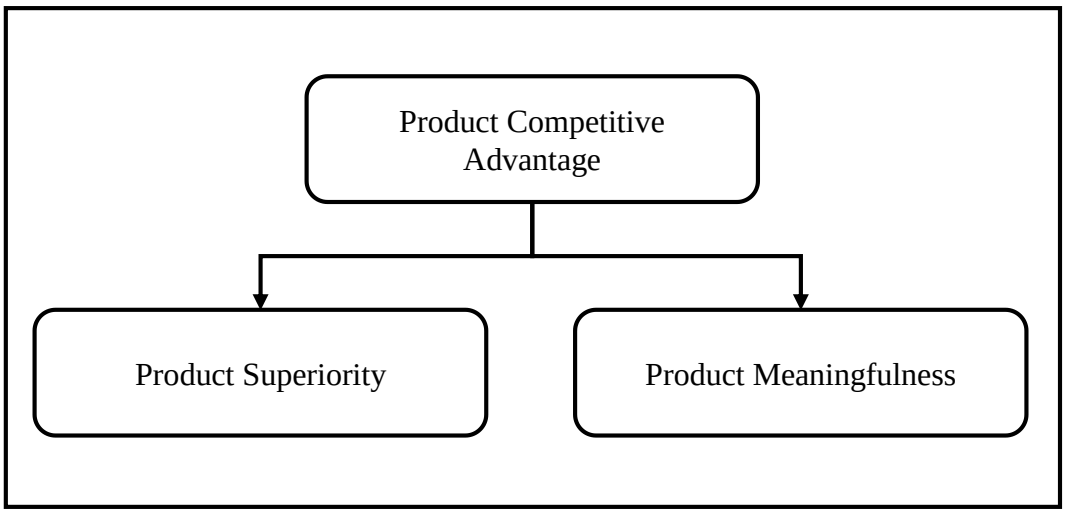

Figure 4: Theoretical construct of product competitive advantage[12]

[12] Figure in reference to Rijsdijk et al. (2011, p. 33ff.).

Product superiority refers to the extent to which a product offers unique performance characteristics, is superior in quality and in meeting the needs of a target audience (e.g., potential investor, scientific community) (Song/Parry 1996, p. 427; Song/Parry 1999, p. 673; Harmancioglu et al. 2009, p. 274; McNally et al. 2010, p. 1000). Product meaningfulness concerns the values, benefits, and advantages target end users receive from using the product (Rijsdijk et al. 2011, p. 33). The particular prominence of research on product competitive advantage in the NPD literature results from the close association of superior and unique products with successful products (see Tables 5 to 12).

In one of the early studies on determinants of industrial new product success, Cooper (1979b, p. 100) observed that product uniqueness and superiority are the most important contributing factors of new product success. In a follow-up study of Cooper/Kleinschmidt (1987), their research study "overwhelmingly points to product advantage as a number one success factor […]." (p. 178). Consistent with these results, the same authors investigated data on new product projects in the chemical industry and identified product advantage as the strongest predictor of success (Cooper/Kleinschmidt 1993). Examining new product ventures in the electronics industry, Zirger/Maidique (1990) found technical performance to be positively related to product success. These results are supported by Song/Parry (1996, 1997b, 1999), who found positive relationships between new product success and multi-item measures of product competitive advantage, as well as Veldhuizen et al. (2006), who observed that a technically superior product is positively associated with product success. Others demonstrated the positive relationship between product competitive advantage and product performance (Li/Calantone 1998; Langerak et al. 2004; Nakata et al. 2006). In addition, McNally et al. (2010) observed that product competitive advantage had a positive impact on the financial performance (i.e., sales and profit) of products from the biochemical, chemical and pharmaceutical industries.

In summary, these research results emphasize the benefits of developing superior, unique and meaningful products. Especially in the biotechnology industry, cooperative R&D projects between biotechnology firms and PRI are in the need to develop products with a competitive advantage in order to attract

investors and thus to survive in the industry (Ernst & Young 2013, p. 31[13]; Ernst & Young 2014, p. 11[14]).

[13] Reference based on an article written by Dr. Jörg Fregien, CEO Life Science Inkubator, Bonn.

[14] Reference based on an article written by Dr. Karsten Henco. Dr. Henco is co-founder or co-founding investor of several biotechnology companies in Germany, USA, Canada and Austria such as Qiagen NV, Evotec AG, NewLab AG, Coley Pharmaceuticals Inc, U3 Pharma AG, Neurimmune Therapeutics AG, Zurich, Switzerland, Medesso GmbH, CT Atlantic AG, HS LifeSciences, AG and QureInvest II SICAR and its portfolio companies.

Table 5: Studies focusing on the relationship between product competitive advantage and new product success measures (I)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Cooper (1979a)	Field study of key informants from 103 Canadian industrial product producers reporting on 102 commercially successful and 93 commercially unsuccessful new industrial product ventures.	ANOVA, correlation analysis	Product competitive advantage was assessed using several single item measures. New product success/failure was defined from the point of view of the firm and in terms of profitability.	Five measures of product competitive advantage (regarding uniqueness, need fulfillment, cost reduction, and quality) were significantly related to new product success or failure.
Cooper (1979b)	Field study of key informants from 103 Canadian industrial product producers reporting on 102 commercially successful and 93 commercially unsuccessful new industrial product ventures.	Linear discriminant analysis	Product uniqueness and superiority was measured by six items concerning innovativeness, uniqueness, cost reduction, need fulfillment and quality relative to competitive offerings. New product success/failure was defined from the point of view of the firm and in terms of profitability.	The single most important new product dimension leading to new product success was product uniqueness and superiority.

Table 6: Studies focusing on the relationship between product competitive advantage and new product success measures (II)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Cooper/Kleinschmidt (1987)	Field study of key informants from 125 industrial product firms reporting on 203 new product projects (123 successes and 80 failures).	One-Way ANOVA, correlation analysis	Product advantage was measured by six items concerning benefits, quality, superiority, and problem-solving capability relative to competitive offerings, reducing customers' costs, and innovativeness. New product success was measured as a dichotomous yes/no measure asking whether or not the product was a financial success (ANOVA), and by ten different measures (e.g., profitability level, payback period, and domestic market share).	New product success was significantly related to product advantage (ANOVA results). Product advantage was positively correlated with profitability level, domestic and foreign market share, relative sales and profits, opportunity window on new categories and new markets, and meeting sales and profits objectives, and negatively correlated with payback period (i.e., product advantage yielded shorter paybacks).

Table 7: Studies focusing on the relationship between product competitive advantage and new product success measures (III)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Zirger/Maidique (1990)	Field study of 86 senior managers reporting on electronics products introduced into the market. (Each manager was asked to report on a pair of products that were financial extremes. The final analysis included 77 successful products and 71 failures).	Multiple discriminant analysis	Product value was measured with three items concerning the price and benefits relative to competitive offerings, as well as a product concept developed from interactions between the product development team, introduction team, and the customers. Superior technical performance was measured by two items concerning the product's technical performance and the coordination between marketing and engineering. The degree of product's success and failure was measured on a ten-point scale ranging from a major financial loss to a major profitability contributor with financial breakeven at its midpoint.	A product providing a significant value (performance to cost) to the customer was positively related to product success and negatively related to product failures. A technically superior product was positively related to product success and negatively related to product failures.

Table 8: Studies focusing on the relationship between product competitive advantage and new product success measures (IV)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Cooper/Kleinschmidt (1993)	Field study of key informants from 21 chemical firms and divisions in the U.S.A., Canada, and Europe reporting on 103 new product projects (68 successes and 35 failures) which had gone to the market.	One-Way ANOVA, correlation analysis	Product Differential Advantage was measured by several single items; not grouped). New product performance included rated profitability, technological success, annual sales revenues from the product, and market shares.	Several single item measures of product differential advantage were positively correlated with new product performance. Product advantage was the number one factor in new product success in the chemical industry.
Parry/Song (1994)	Field study of new product development managers from 129 Chinese state-owned-enterprises providing information about 258 product successes and failures. Of these, 250 were industrial products, and the remainder were consumer goods.	Correlation analysis	Relative Product Advantage was measured by five items concerning uniqueness, costs reduction, as well as quality and need fulfillment relative to competitive offerings New product success was assessed by asking the respondents to indicate the relative success of the new product in terms of profitability.	Relative product advantage was positively correlated with new product success.

Table 9: Studies focusing on the relationship between product competitive advantage and new product success measures (V)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song/Parry (1996)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Correlation analysis	Product advantage was measured by seven items concerning uniqueness, need fulfillment, reducing customers' costs, newness, quality, benefits, and technical performance relative to competitive offerings. New product success measures included product profitability, relative sales performance, relative market share, and the degree to which a product opened a window of opportunity for the respondent firm.	Product advantage was positively correlated with new product success.
Song/Parry (1997b)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Path analysis using the maximum likelihood estimation procedure in LISREL	Product competitive advantage was measured by five items concerning uniqueness, need fulfillment, newness, quality, and technical performance relative to competitive offerings. Relative new product success was measured by four items concerning overall profitability, relative sales performance to the firm's other new products, relative profitability to the firm's other new products, and relative profitability to the firm's objectives for this product.	The level of product competitive advantage positively and significantly affected the level of relative new product success.

Table 10: Studies focusing on the relationship between product competitive advantage and new product success measures (VI)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Li/ Calantone (1998)	Field study of presidents and chief executive officers from 236 software firms reporting on a new software product the company's development program had introduced into the U.S. market.	Generalized Least Squares method in EQS	New product advantage was measured by seven items concerning newness, productivity, uniqueness, reliability, compatibility, functionality, and ease of use. Product market performance: Two judgmental measures to assess the company's software market performance on before-tax profit and return on investment, relative to its competition. Two objective measures of firm's actual dollar share of the served market and pre-tax profit margin.	The greater the new product advantage, the better the product market performance was.
Langerak et al. (2004)	Field study of 126 knowledgeable informants from Dutch firms in the primary metal, fabricated metal, machinery equipment, electrical equipment, transportation equipment, and measuring instruments industries reporting on new products.	Structural equation modeling by means of LISREL	Product advantage refers to the benefits that customers get from the new product. New product performance consisted of five subscales reflecting the dimensions of market level, financial, customer acceptance, product level, and timing measures of NPD success.	Product advantage had a positive and significant relationship with new product performance.

Table 11: Studies focusing on the relationship between product competitive advantage and new product success measures (VII)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Nakata et al. (2006)	Field study of 149 Korean and 110 Japanese marketing or product managers from manufacturing firms reporting on injecting advantage into recent new products.	Path analysis using ordinary least squares regressions	New product advantage was measured by eight items concerning uniqueness, need fulfillment, utility, quality, benefits, problem-solving capability, innovativeness, and radical difference relative to competitive offerings. New product performance was measured by five items concerning relative market share, relative sales, and relative profitability.	Higher new product advantage was positively associated with greater new product performance in both Korea and Japan.
Veldhuizen et al. (2006)	Field study of 86 senior managers reporting on electronics products introduced into the market. (Each manager was asked to report on a pair of products that were financial extremes. The final analysis included 77 successful products and 71 failures).	Multiple discriminant analysis	Product value was measured with three items concerning the price and benefits relative to competitive offerings, a product concept developed from interactions between the product development team, introduction team, and the customers. Superior technical performance was measured by two items concerning the product's technical performance and the coordination between marketing and engineering. The degree of product's success and failure was measured on a ten-point scale ranging from a major financial loss to a major profitability contributor with financial breakeven at its midpoint.	A product providing a significant value (performance to cost) to the customer was positively related to product success and negatively related to product failures. A technically superior product was positively related to product success and negatively related to product failures.

Table 12: Studies focusing on the relationship between product competitive advantage and new product success measures (VIII)

Study	Empirical Setting	Method	Operationalization	Empirical Results
McNally et al. (2010)	Field study of NPD managers, product development managers, product line managers, and product managers from the biochemical, chemical, and pharmaceutical industries in North America reporting on 444 new product launches.	Structural equation modeling	Product advantage was measured by three items concerning superiority over other products in terms of meeting customer's needs, product quality, and unique attributes or performance characteristics. Product financial performance was measured by two items related to the product's sales and profits.	Product advantage has a positive impact on product financial performance.

2.1.2 Project-related Factors

Project-related factors in NPD refer to the fit of available resources and skills with the needs of an NPD venture (see Figure 5). The investigation of the match of capabilities and assets with project needs can be traced back to the works of Robert G. Cooper, whose earlier studies focused on studying the causes of failure of new industrial products (Cooper 1975). A few years later, Cooper (1979a, p. 128f.) examined commercially successful and unsuccessful new industrial product ventures in Canada. He found that a key determining factor of new product success is the fit between a company's resources and skills with the needs of the NPD project. In particular, the fit of available technical resources and skills and marketing resources and skills with a project's needs were positively associated with success of new products.

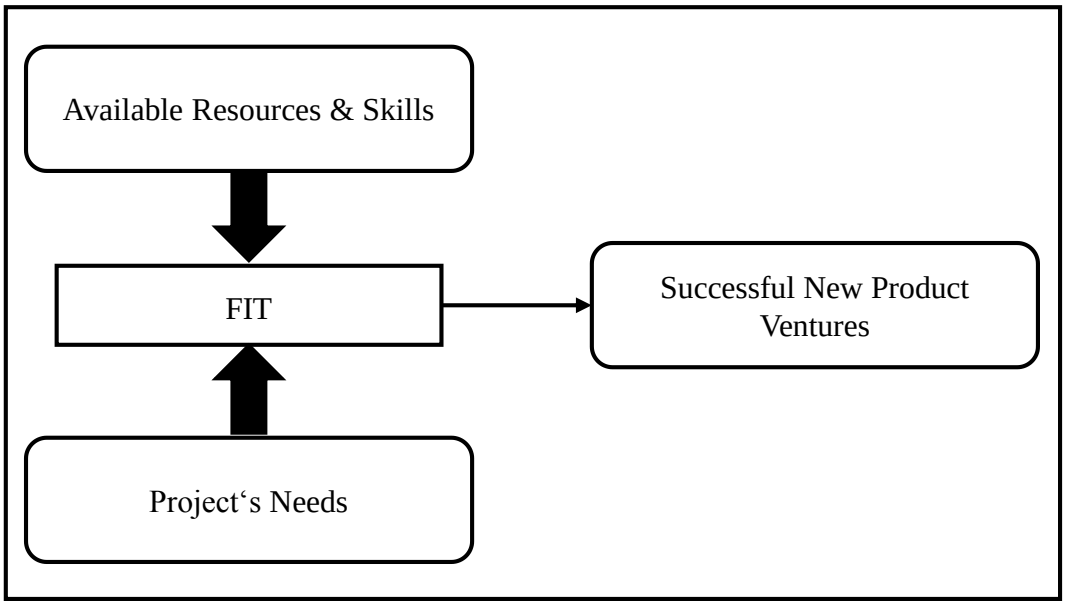

Figure 5: Project-related factors and successful new product ventures[15]

Following studies adopted the concept of fit and investigated the adequacy of available resources and skills with the achievement of a product competitive advantage (see Table 13 and Table 14). For instance, Song/Parry (1996; 1997b) investigated in their field study of project managers from 404 Japanese non-service companies the adequacy of technical and marketing capabilities and assets possessed by 788 new physical product development projects. The authors found that the level of adequacy of a company's resources and skills with the product venture positively affected the level of product competitive advantage. In another field study of North American firms (e.g., in the chemical industry), Harmancioglu et al. (2009) examined the fit of available resources and skills with the needs of 306 NPD ventures. Their research results also showed that marketing fit and technological fit was positively associated with new product advantage.

[15] Figure in reference to the NPD literature (e.g., Song/Parry 1996; Song/Parry 1997b; Harmancioglu et al. 2009).

Table 13: Studies focusing on the relationship between resources & skills and product competitive advantage (I)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song/Parry (1996)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Correlation analysis	Marketing synergy was measured by six items concerning the adequacy of a company's resources and skills (i.e., marketing research, salesforce, and distribution) for the NPD project. Technological synergy was measured by six items concerning the adequacy of a company's resources and skills (i.e., R&D, engineering, and manufacturing) for the NPD project. Product advantage was measured by seven items concerning uniqueness, need fulfillment, reducing customers' costs, newness, quality, benefits, and technical performance relative to competitive offerings.	The level of marketing synergy and the level of technical synergy were positively correlated with product advantage.
Song/Parry (1997b)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Path analysis using the maximum likelihood estimation procedure in LISREL.	Technological synergy was measured by four items concerning the adequacy of a company's resources and skills (i.e., R&D and engineering) for the NPD project. Product competitive advantage was measured by five items concerning uniqueness, need fulfillment, newness, quality, and technical performance relative to competitive offerings.	The level of technical synergy positively and significantly affected the level of product competitive advantage.

Table 14: Studies focusing on the relationship between resources & skills and product competitive advantage (II)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Harmancioglu et al. (2009)	Field study of respondents (e.g., in marketing, R&D, and general management) from North American firms (e.g., in the chemical industry) reporting on 306 recent new products on the market previously not produced or sold by their company.	Partial least squares analysis	Marketing fit was measured by three items encompassing fit with advertising, promotion, and market research resources. Technological fit was measured by three items regarding existing technologies, R&D expertise and manufacturing skills. New product advantage was measured by three items concerning need fulfillment, quality, and uniqueness relative to competitive offerings.	Marketing fit and technological fit were positively related to new product advantage.

Moreover, Calantone et al. (1996) argued that marketing fit (i.e., adequacy of available marketing-related resources and skills with the needs of an NPD venture) and technical fit (i.e., adequacy of available technical resources and skills with the needs of an NPD venture) are associated with successful new product ventures "only indirectly through proficiency of NPD activities" (Calantone et al. 1996, p. 343). Figure 6 illustrates this relationship between project-related factors, proficiency in NPD activities, and successful new product ventures proposed by Calantone et al. (1996).

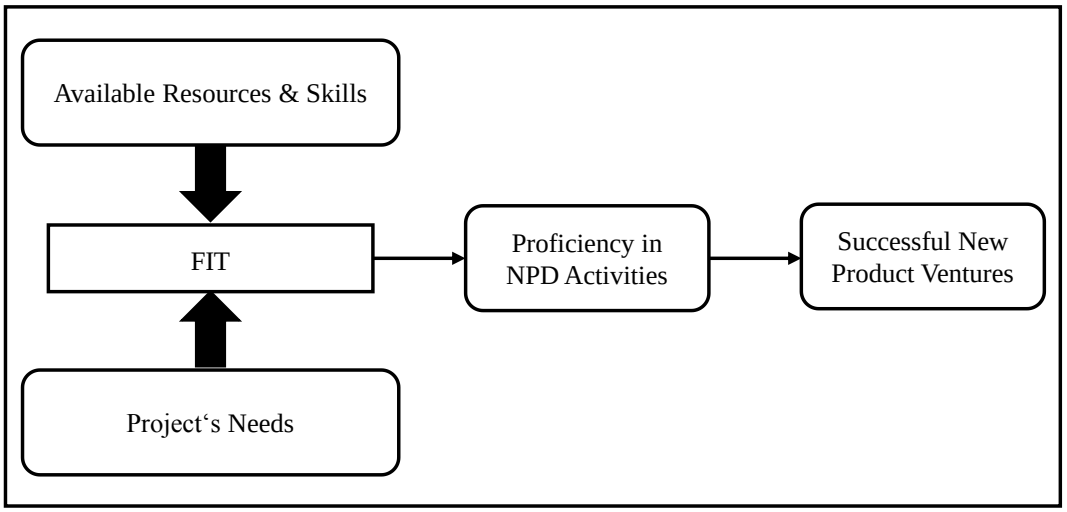

Figure 6: Project-related factors, proficiency in NPD activities, and successful new product ventures[16]

Consequently, a stream of studies investigated the proposed relationship of fit of resources and skills with proficiency in conducting NPD activities (e.g., prototype development). Studying 142 tangible NPD projects of Chinese firms, the results of Calantone et al. (1996) indicated that adequate skills and resources in a project are related to proficiency in NPD activities. Supporting these research findings, Song et al. (1997b) observed that the level of fit of resources and skills with the project needs was associated positively with the level of proficiency in marketing activities in 307 physical new NPD venture in Taiwan. Investigating success and failure of NPD projects of large Japanese firms, Song et al. (1997b) demonstrated that the alignment of skills and project needs positively affected the level of marketing proficiency. The positive relationship between adequate skills and resources and proficiency in NPD activities was also replicated by Song/Parry (1997a, b), using a sample of 312 U.S. firms reporting on 612 new physical product development projects, as well as 788 new physical product development projects of Japanese non-service companies. Tables 15 to 18 summarize the above-discussed research findings concerning project-related factors affecting proficiency in NPD activities.

In summary, empirical studies in NPD research indicate that sources of product competitive advantage are the resources and skills which are available in a development project (e.g., Song/Parry 1996; Song/Parry 1997b; Harmancioglu

[16] Figure in reference to Calantone et al. (1996).

et al. 2009). Other studies in NPD research suggest that the available skills and resources are indirectly associated with product competitive advantage through the proficient execution of development activities (e.g., Calantone et al. 1996; Song et al. 1997a, b; Song/Parry 1997a, b).

Table 15: Studies focusing on the relationship between technical/marketing fit and proficiency in technical/marketing activities (I)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Calantone et al. (1996)	Field study of NPD managers from U.S. firms principally involved in the manufacture and sale of tangible products reporting on 142 NPD projects and NPD managers from Chinese firms reporting on 470 NPD projects.	Path analysis	Marketing skills and resources was measured by four items concerning the adequacy of a company's resources and skills (i.e., marketing research, sales force and/or distribution, advertising and promotion, and management) for the NPD project. Technical skills and resources was measured by two items concerning the adequacy of a company's skills and people (i.e., R&D and engineering) for the NPD project. Proficiency in marketing activities was measured by five items concerning how well several marketing activities (e.g., preliminary assessment of the market) were undertaken. Proficiency in technical activities was measured by five items concerning how well several technical activities (e.g., R&D) were undertaken.	Adequate technical and marketing skills and resources in a project were positively related to proficiency in technical and marketing activities, respectively.

Table 16: Studies focusing on the relationship between technical/marketing fit and proficiency in technical/marketing activities (II)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song et al. (1997a)	Field study of project managers reporting on 372 recently developed South Korean new physical products and 306 recently developed Taiwanese new physical products.	Three-stage least squares regression	Marketing resources synergy was measured by four items concerning the adequacy of a company's resources (i.e., marketing research, sales force, distribution, and advertising/promotion) for the NPD project. Marketing skills synergy was measured by four items concerning the adequacy of a company's skills (i.e., marketing research, sales force, distribution, and advertising/promotion) for the NPD project. Marketing activities proficiency was measured by ten items concerning how well several marketing activities (e.g., preliminary assessment of the market) were undertaken.	The level of marketing resources synergy and the level of marketing skills synergy were associated positively with the level of proficiency in marketing activities only in the Taiwanese sample.

Table 17: Studies focusing on the relationship between technical/marketing fit and proficiency in technical/marketing activities (III)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song et al. (1997b)	Field study of development and marketing teams from 17 large, multi-divisional Japanese firms reporting on 65 completed NPD projects (34 successes and 31 failures).	Path analysis	Skills/needs alignment was measured by four items concerning the adequacy of a company's skills (i.e., marketing, R&D, engineering, and manufacturing) for the NPD project. Marketing proficiency was measured by four items concerning how well several marketing activities (e.g., exploratory stage activities) were undertaken.	Skills/needs alignment positively affected the level of marketing proficiency.
Song/Parry (1997a)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects and project managers from 312 U.S. firms reporting on 612 new physical product development projects.	Ordinary least squares regression	Marketing skills and resources was measured by ten items concerning the adequacy of a company's marketing resources and skills for the NPD project. Technical skills and resources was measured by six items concerning the adequacy of a company's resources and skills for the NPD project. Proficiency in the NPD process was measured by activities representing the stages of idea development and screening, business and market opportunity analysis, technical development, product testing, and product commercialization.	Marketing skills and resources was positively related to proficiency in the following stages of the NPD process: (a) idea development and screening, (b) business and market opportunity analysis, (c) product testing, and (d) product commercialization. Technical skills and resources was positively related to proficiency in the technical development stage of NPD.

Table 18: Studies focusing on the relationship between technical/marketing fit and proficiency in technical/marketing activities (IV)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song/Parry (1997b)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Path analysis using the maximum likelihood estimation procedure in LISREL.	Marketing synergy was measured by four items concerning the adequacy of a company's resources and skills (i.e., salesforce, distribution, and advertising/promotion) for the NPD project. Technological synergy was measured by four items concerning the adequacy of a company's resources and skills (i.e., R&D and engineering) for the NPD project. Marketing proficiency was measured by four items concerning how well several marketing activities (e.g., exploratory stage activities) were undertaken. Technical proficiency was measured by six items concerning how well several technical activities (e.g., prototype testing) were undertaken.	The level of marketing synergy and the level of technical synergy positively affected the level of marketing proficiency and the level of technical proficiency, respectively.

2.1.3 Process-related Factors

Process-related factors refer to proficiency in performing marketing and technical activities. These factors are concerned with "how well or adequately" various

marketing and technical activities are executed (Song/Parry 1997a, p. 13). As discussed before, Calantone et al. (1996, P. 343) argued that proficiency in NPD activities is an essential mediating factor that explains the association between a project's available resources and skills with successful NPD ventures.[17] Therefore, a stream of studies investigated the relationship between the proficient execution of various marketing-related and technical activities with achieving a product competitive advantage.

One of these investigations includes the field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects conducted by Song/Parry (1996; 1997b). An initial correlation analysis showed that proficiency in the predevelopment planning process, concept development and evaluation, market research, pretesting and technical activities, as well as market launch proficiency, were positively related to product competitive advantage (Song/Parry 1996). Further, a subsequent path analysis demonstrated that the level of marketing and technical proficiency positively affected the level product competitive advantage (Song/Parry 1997b).

In a field study of 149 Korean and 110 Japanese marketing or product managers from manufacturing firms, Nakata et al. (2006) found that efficacy in carrying out NPD activities was positively associated with new product advantage. The positive relationship between the proficient execution of marketing activities was also demonstrated by Harmancioglu et al. (2009), investigating a sample of respondents from North American firms (e.g., in the chemical industry) reporting on 306 recent new products.

In summary, empirical studies in NPD research suggest that the proficient execution of R&D activities positively influences product competitive advantage (e.g., Song/Parry 1996; Song/Parry 1997b; Nakata et al. 2006; Harmancioglu et al. 2009). Tables 19 to 22 summarize the above-discussed research findings concerning process-related factors affecting product competitive advantage.

[17] Please also see Figure 6 from the previous section.

Table 19: Studies focusing on the relationship between proficiency in the NPD process and product competitive advantage (I)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song/Parry (1996)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Correlation analysis	Proficiency in the NPD process was measured by activities representing the sub-processes of predevelopment planning (five items), concept development and evaluation (six items), market research (three items), pretesting (six items), and market launch (four items). Technical proficiency was measured by six items concerning how well several technical activities (e.g., prototype testing) were undertaken. Product advantage was measured by seven items concerning uniqueness, need fulfillment, reducing customers' costs, newness, quality, benefits, and technical performance relative to competitive offerings.	Proficiency in the predevelopment planning process, proficiency in concept development and evaluation, proficiency in market research, pre-test proficiency, technical proficiency, and market launch proficiency were positively correlated with product advantage.

Table 20: Studies focusing on the relationship between proficiency in the NPD process and product competitive advantage (II)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Song/Parry (1997b)	Field study of project managers from 404 Japanese non-service companies reporting on 788 new physical product development projects.	Path analysis using the maximum likelihood estimation procedure in LISREL.	Marketing proficiency was measured by four items concerning how well several marketing activities (e.g., exploratory stage activities) were undertaken. Technical proficiency was measured by six items concerning how well several technical activities (e.g., prototype testing) were undertaken. Product competitive advantage was measured by five items concerning uniqueness, need fulfillment, newness ("to do something which could not be done before"), quality, and technical performance relative to competitive offerings.	The level of marketing proficiency and the level of technical proficiency positively affected the level product competitive advantage.

Table 21: Studies focusing on the relationship between proficiency in the NPD process and product competitive advantage (III)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Nakata et al. (2006)	Field study of 149 Korean and 110 Japanese marketing or product managers from manufacturing firms reporting on injecting advantage into recent new products.	Path analysis using ordinary least squares regressions	New product team proficiency was measured by five items encompassing dimensions such as technical skills, marketing knowledge, and team efficiency in the group responsible for developing a new product. New product advantage was measured by eight items concerning uniqueness, need fulfillment, utility, quality, benefits, problem-solving capability, innovativeness, and radical difference relative to competitive offerings.	New product team proficiency was positively associated with new product advantage in both Korea and Japan.

Table 22: Studies focusing on the relationship between proficiency in the NPD process and product competitive advantage (IV)

Study	Empirical Setting	Method	Operationalization	Empirical Results
Harmancioglu et al. (2009)	Field study of respondents (e.g., in marketing, R&D, and general management) from North American firms (e.g., in the chemical industry) reporting on 306 recent new products on the market previously not produced or sold by their company.	Partial least squares analysis	Marketing execution proficiency was measured by five items concerning how well several marketing activities (e.g., preliminary market assessment) were undertaken. Technical execution proficiency was measured by four items concerning how well several technical activities (e.g., prototype development) were undertaken. New product advantage was measured by three items concerning need fulfillment, quality, and uniqueness relative to competitive offerings.	Marketing execution proficiency was positively related to new product advantage. Technical execution proficiency was not related to new product advantage.

2.2 The Biotechnology Industry

2.2.1 Characteristics

Biotechnology is defined as the "application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or non-living materials for the production of knowledge, goods and services" (OECD

2005, p. 9). The biotechnology industry is a new, relatively young industry that focuses on the economic exploitation of biotechnology (Schüler 2016, p. 3).

As an interdisciplinary technology, biotechnology and its economic application have a broad spectrum of applications. These applications range from the pharmaceutical, chemical, agricultural and food sectors to environmental protection. The different areas of application have been assigned colors over time. A very rough distinction is made between red biotechnology, white biotechnology and green biotechnology (Müller 2007, p. 385; Schüler 2016, p. 143). Red biotechnology refers to activities in the area of health/medicine (i.e., "the development of therapeutics and/or diagnostics for the field of human medicine, drug delivery, human tissue replacement" (BIOCOM AG 2015, p. 10). White biotechnology refers to industrial biotechnology (i.e., development of biotechnological materials and processes for the handling of waste or sewage, for chemical synthesis, for the extraction of raw materials and energy etc.; BIOCOM AG 2017, p. 13). Green biotechnology refers to agricultural biotechnology (i.e., development of "[g]enetically modified plants, animals or microorganisms, as well as nongenetically modified plants grown using biotechnological procedures, for use in agriculture or forestry"; BIOCOM AG 2017, p. 13).

NPD development in the biotechnology industry - especially the development of a drug - is heavily science-based and considered to be tedious, risky and expensive (Schüler 2016, p. 167ff). There is actually no other product that is as complex to develop as drugs, especially due to extensive human testing studies and very strict market approval requirements. It takes twelve to fifteen years from the initial idea or concept to reach the market. The first five years are spent on research and preclinical studies[18], the clinical trial takes another five to eight years and the approval one to two years (Schüler 2016, p. 167).

[18] Preclinical trials refer to testing of potential compounds in vitro, on bacteria, cell and tissue cultures, and isolated organs (efficacy, toxicity, pharmacokinetics), tests on the animal organism (at least two to three animal species), development of adequate dosage forms (galenics) (Schüler 2016, p. 169).

The overall probability of obtaining marketing approval for a newly developed drug from phase I[19] onwards is 10% to 20%, and from research/preclinical trials only around 5%. In order to bring a new drug to market successfully, ten to twelve drug candidates have - from a statistical point of view – to be tested in preclinical trials, five to ten in phase I, three to seven in phase II[20] and one to two in phase III[21]. Even in phase III studies, the average risk of default is still 50%. In the final approval phase, there is still the possibility of rejection by the Food and Drug Administration (FDA), which can be as high as 10 to 20% (Schüler 2016, p. 171).

In addition to the long duration and high risk of drug development, the immense costs have also to be considered. Development costs vary between US$ 1.5 billion and US$ 2.5 billion, depending on the calculation basis and method (DiMasi 2003; Paul et al. 2010; Mestre-Ferrandiz 2012, DiMasi et al. 2016). Schüler (2016) points out that the direct costs for R&D of a successful compound amount to only 15 to 30% of the total costs. The remaining costs concern (but are not limited to) expenses for failed R&D ventures. These expenses are taken into account when estimating the total costs, since a single R&D project is usually not sufficient to successfully develop a marketable product and thus, high failure rates of R&D ventures have to be considered. In addition to these "real" costs, the cost of capital and the time value of money have to be taken into account (Schüler 2016, p. 174f.).

This brief introduction regarding the characteristics of the biotechnology industry is followed by a section illustrating the industry's strong dependence on cooperative R&D ventures between biotechnology firms and PRI (Ortiz 2013, p. 223f.; BIOCOM AG 2015, p. 17).

[19] Phase I refers to tolerance tests with healthy subjects, determination of side effects and dosages (Schüler 2016, p. 169).

[20] Phase II refers to efficacy tests on a smaller number of selected patients, confirmation of efficacy (i.e., proof of concept), further determination of side effects and determination of the optimal dosage (Schüler 2016, p. 169).

[21] Phase III refers to tests on many patients (efficacy, tolerability and possible interactions with other drugs among many different patients) (Schüler 2016, p. 169).

2.2.2 R&D Cooperations in the Biotechnology Industry

This section synthesizes state of the art research on R&D cooperations in the biotechnology industry. NPD in the biotechnology industry can be distinguished into exploration and exploitation processes (Powell et al. 1996, p. 124f.; Rothaermel/Deeds 2004, p. 201ff.). Exploration is "the pursuit of new knowledge, of things that might come to be known", while exploitation describes "the use and development of things already known" (Levinthal/March 1993, p. 105). Exploration implies basic research and risk-taking in order to discover something new (Koza/Lewin 1998, p. 256f.). The anticipated outcome of the exploration process can be the codification of new knowledge through patenting and a prototype product as the basis for further testing and development processes. The exploration process is typically characterized by cooperative R&D projects between biotechnology firms and PRI (Rothaermel/Deeds 2004, p. 204). Exploitation in the biotechnology industry involves tremendous and costly testing efforts until a prototype results in a marketable product. This resource-intensive exploitation process is typically characterized by inter-firm cooperations between small and medium-sized biotechnology firms and established (pharmaceutical) companies (Rothaermel 2001, p. 687ff.).

Starting with the latter, research on inter-firm cooperations in biotechnology is covered in the strategic alliances literature. Studies of inter-firm cooperations in the biotechnology industry can be distinguished into three broad research streams (Stuart et al. 2007, p. 477ff.). The first research stream is engaged in testing theories of alliance formation (e.g., Walker et al. 1997). The second research stream focuses on conditions and motives that explain governance choices of collaborative relationships (e.g., Pisano 1989, 1991; Robinson/Stuart 2007). The third research stream deals with the consequences of cooperations in the biotechnology industry such as valuations of young and publicly-traded biotechnology firms that cooperate with prominent strategic alliance partners (e.g., Stuart et al. 1999).

Research on the linkages between biotechnology firms and PRI is primarily featured in the literature on university-industry relations (Stuart et al. 2007, p. 479). Several studies examined university-industry relations in

biotechnology on the industry level. For instance, research investigated the importance of public science (i.e., knowledge that originates from PRI) in the biotechnology industry (McMillan et al. 2000) and university research commercialization in the life sciences (Owen-Smith/Powell 2003). A notable amount of studies conducted by Zucker and colleagues focused on the role of universities and star scientists in the development of the American and Japanese biotechnology industry. These researchers studied the association of star scientists` geographic locations with those of American biotechnology firms (Zucker, Darby, & Brewer 1998), the impact of collaborations between university star scientists and biotechnology firms on several performance measures (Zucker, Darby, & Armstrong 1998; Zucker/Darby 2001; Zucker, Darby, & Armstrong 2002), as well as the transfer of university star scientists to firms (Zucker, Darby, & Torero 2002). Similarly, Stuart/Ding (2006) examined the social antecedents that lead US-university scientists to become biotechnology entrepreneurs.

There are also studies focusing on the project level but reviewing state-of-the-art-literature revealed that research on this level is relatively scarce. A notable example of research on the project level is the study of Ortiz (2013), who focused on the regional biotechnology cluster in Munich. In accordance with a resource-based perspective, the author’s qualitative research confirmed that biotechnology firms and PRI cooperate in R&D projects to complement their own resources and knowledge (Ortiz 2013, p. 281ff.).

Despite several studies on R&D cooperations in the biotechnology industry, extant research has neglected to provide empirical evidence that the synergy or fit of resources and skills (project-related factors) actually impacts success of cooperative R&D projects. Moreover, extant literature has neglected to investigate technical and marketing activities (process-related factors) in cooperative R&D projects between PRI and biotechnology firms. These activities have been given considerable attention in the literature on success of industrial new products (see Section 2.1). However, the extant literature on cooperations in the biotechnology industry is limited to the discussion that firms need to cooperate with PRI in order to complement the own resources and skills. The role of technical (e.g., prototype testing) and marketing activities (e.g., market research) in cooperative R&D projects between biotechnology firms and PRI remains

unclear. Research on such controllable activities would not only contribute to the existing literature but also be of value to practitioners. Since the transformation of biotechnology into an industry in the 1980s, hundreds of firms have been founded in Germany and many more abroad. Consequently, competition grows and research needs to focus on controllable factors that impact the achievement of a product competitive advantage.

3 A Model of Determinants of Success from a Product Competitive Advantage Perspective

The overall research objective of this thesis is to identify and empirically test the determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. In particular, this thesis aims to answer the following questions:

- What are the theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?
- What are the project-related and process-related factors affecting product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?
- How are these determinants interrelated and in which ways do they contribute to the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI?

By drawing from theoretical foundations of resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978), as well as research on NPD, a conceptual model will be developed in this section in order to be able to conduct the subsequent empirical analysis which allows to answer these questions.

This section is divided into three parts. First, the underlying theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI are presented (Section 3.1). These theoretical foundations involve resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978). Second, the conceptual model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective is developed (Section 3.2). Third, the hypotheses of this thesis are formulated with regard to the research model (Section 3.3).

3.1 Theoretical Framework

Scholars in the realm of strategic management have always been interested in explaining differential organizational performance (Rumelt et al. 1991, p. 6ff.). Two dominant perspectives have emerged regarding the achievement of competitive advantages (Dyer/Singh 1998, p. 660). The first - the industry structure view or perspective - assumes that competitive advantages are "primarily a function of a firm's membership in an industry with favorable structural characteristics (e.g., relative bargaining power, barriers to entry, and so on)" (Dyer/Singh 1998, p. 660). Research following this perspective on competitive advantages focuses on the industry as the relevant unit of analysis (Dyer/Singh 1998, p. 660).

However, this thesis focuses on the cooperative R&D project between biotechnology firms and PRI as the relevant unit of analysis. Therefore, the present investigation takes on the second dominant perspective, which considers the organization as the relevant unit of analysis when searching for sources of competitive advantage (Dyer/Singh 1998, p. 660; e.g., Tushman/Nadler 1978; Barney 1991; Peteraf 1993). Conducting research on the organizational or project level guides the choice of theory in the present study and its attempt to explain the achievement of a product competitive advantage.

Cooperative R&D projects can be regarded as temporary forms of organization (Cattani et al. 2011, p. xvi). These cooperative R&D projects are established in order to gain access to the partner's highly specialized resources and skills which are not available or possessed by the internal R&D division but are essential to create superior value (e.g., a superior product) (Rothaermel/Deeds 2004, p. 204; Ortiz 2013, p. 281f.). From this perspective on cooperative R&D projects between biotechnology firms and PRI, the achievement of a product competitive advantage is explained through the exploitation of resources and skills. The underlying theoretical assumptions are provided by resource-based theory (Barney 1991; Peteraf 1993).

Under the premise of this thesis that cooperative R&D projects are temporary organizations, it is also important to consider how organizations

function. According to the seminal work of Tushman/Nadler (1978) on organizational design, organizations face several sources of uncertainty in their work-related environment (e.g., technology) to which they have to respond to. Organizations are information-processing systems with the task of collecting, gathering, and processing information in order to reduce the uncertainties they are confronted with (Tushman/Nadler 1978, p. 614; Rogers et al. 1999, p. 568). Likewise, cooperative R&D project teams need to gather, interpret, and utilize information in order to effectively cope with several sources of uncertainty (e.g., with regard to the applied technology) in the process of developing a meaningful and superior product. From this perspective on cooperative R&D projects between biotechnology firms and PRI, the achievement of a product competitive advantage is explained through the venture's capability of processing information. The underlying theoretical assumptions are provided by information-processing theory (Tushman/Nadler 1978; Daft/Lengel 1986; Sinkula 1994; Song et al. 2005).

The following sections explain resource-based theory and information-processing theory in more detail.

3.1.1 Resource-based Theory

In the academic literature, resource-based theory (Draulans et al. 2003, p. 153; Saxton 1997, p. 445) is also referred to as resource-based view (Barney 1991, p. 100ff.; Eisenhardt/Schoonhoven 1996, p. 136ff.; Eisenhardt/Martin 2000, p. 1105ff.; Barney 2001, p. 643ff.; Barney et al. 2001, p. 625ff.) or resource-based perspective (Bhatt 2000, p. 119ff.). The conceptual foundation for the development of resource-based theory was created by Penrose (1959). Penrose (1959) was one of the first to consider an organization as a bundle of heterogeneous resources. Based on Penrose's approach, Wernerfelt (1984) also emphasized that the source of lasting competitiveness lies in the organization's specific resources. In 1991, Barney (1991) argued that competitive advantages result from an organization's resources and capabilities that are valuable, rare, imperfectly imitable, and not substitutable (Barney et al. 2001, p. 625).

The resource-based view of competitive advantage focuses on the link between an organization's characteristics (i.e., resources and capabilities) and

performance (i.e., competitive advantage) (Barney 1991, p. 101). The theory is based on the assumption that organizations within an industry (e.g., biotechnology industry) are heterogeneous in terms of the resources they control. The resource-based model investigates the implications of this assumption for the analysis of sources of competitive advantages (Barney 1991, p. 101). Before discussing the link between an organization's resources and the achievement of competitive advantages, several concepts that are central to the perspective of resource-based theory of competitive advantage (Barney 1991) need to be addressed. Specifically, the theory's conception of resources, organizations, and competitive advantages need to be briefly illustrated.

Resource-based theory is grounded on a broad understanding of the term resource. A resource is anything that is controlled by and can be considered as a strength of a given organization (Wernerfelt 1984, p. 172; Barney 1991, p. 101; Eisenhardt/Schoonhoven 1996, p. 137). In particular, it is distinguished between tangible and intangible resources (Eisenhardt/Schoonhoven 1996, p. 137; Barney et al. 2001, p. 625). Tangible resources refer to physical resources such as machinery and financial resources. Intangible resources refer to knowledge such as scientific expertise (Eisenhardt/Schoonhoven 1996, p. 137). Some scholars - instead of using the terms of tangible and intangible resources - refer to resources and capabilities (Brush/Artz 1999, p. 225ff.; Bhatt 2000, p. 120), whereas the latter can be regarded as analogous to know-how and skills (Bhatt 2000, p. 119). For instance, know-how and skills in molecular biology can be regarded as a capability of an organization in the biotechnology industry (Eisenharrdt/Martin 2000, p. 1107).

In resource-based theory, an organization – as the value-creating entity – is viewed as a nexus or bundle of resources and capabilities (Penrose 1959, p. 24f.; Lado et al. 1992, p. 78; Bhatt 2000, p. 119; Eisenhardt/Martin 2000, p. 1105; Draulans et al. 2003, p. 153). In this thesis, a cooperative R&D project is regarded as a temporary form of organization (Cattani et al. 2011, p. xvi) in which the partners' complementary resources and skills are combined in order to create superior value (e.g., a superior product) (Rothaermel/Deeds 2004, p. 204; Ortiz 2013, p. 281f.).

The definition of competitive advantage focuses on an organization's (or its products in this thesis) competitive position vis-à-vis potential and existing competitors (or its products) in an industry (Barney 1991, p. 102). In other words, the term competitive advantage refers to the superior value creation of an organization (e.g., a superior product) relative to its existing and potential competitors in a (product) market (Peteraf/Barney 2003, p. 311).

As mentioned briefly at the beginning, the statements of the theory are based on the conviction that competitive advantages of an organization require a certain degree of heterogeneity and immobility of resources (Barney 1991, p. 103ff.). If organizations in a given market possessed completely identical resources or bundles of the various resources (i.e., resource homogeneity), they would all be able to "improve their efficiency and effectiveness in the same way, and to the same extent" (Barney 1991, p. 104). Hence, in such kind of markets, it is not possible for an organization to obtain a competitive advantage over competitors (Barney 1991, p. 104). The requirement for resources and capabilities to be immobile to some degree to obtain a competitive advantage stems from the rationale that in the event of perfectly mobile resources, every organization could potentially acquire any resource, which in turn would lead to resource homogeneity (Barney 1991, p. 104).[22] Indeed, the biotechnology industry is characterized by such a resource heterogeneity and immobility. Resource heterogeneity and immobility are major reasons why cooperative R&D projects are established. Biotechnology firms and PRI cooperate in order to gain access to highly specialized resources and skills they do not possess on their own (Ortiz 2013, p. 281f.). To ensure a certain degree of immobility of these resources and skills, cooperative R&D projects are usually regulated by contracts (e.g., in the form of non-disclosure agreements or license agreements; Ortiz 2012, p. 240).

Given a certain degree of resource homogeneity and immobility, the resource-based theory of competitive advantage postulates that competitive advantages result from an organization's resources and capabilities that are valuable, rare, imperfectly imitable, and not substitutable (Barney et al. 2001, p. 625). To begin with, resource-based theory argues that resources and capabilities

[22] See Barney (1991, p. 105f.) for a detailed discussion on resource homogeneity and mobility.

can only be a source of competitive advantage if they are valuable (Barney 1991, p. 106). Such valuable resources and capabilities enable an organization to participate in its product market more efficiently (Barney 1991, p. 101; Peteraf/Barney 2003, p. 316). More efficiently in this context refers to the organization's ability to produce more economically and/or better satisfy end user (e.g., customer) needs (Peteraf/Barney 2003, p. 311). However, Barney (1991, p. 106) argued in his seminal article on resource-based theory, that valuable resources and capabilities cannot be a source of competitive advantage when they are also held by a large number of existing or potential competitors. If a certain valuable resource is possessed by various organizations, each of these organizations would have the ability to exploit that resource in the same way, hence no organization would be able to produce more economically and/or better satisfy end user than its competitors (Barney 1991, p. 106). Thus, resources and capabilities can only be sources of competitive advantage when they are valuable and rare at the same time (Peteraf/Barney 2003, p. 316).[23] These basic requirements to obtain a competitive advantage are typically met by cooperative R&D projects between biotechnology firms and PRI, since they are initiated with the motivation to gain access to the valuable and rare resources and/or capabilities of partner organizations (Ortiz 2012, p. 281f.).

Barney (1991, p. 107f.) notes that in the medium to long-term, a rare resource or capacity must not simply be imitable in order to be a source of competitive advantage. If a resource or capacity can be imitated, it loses its rarity status. One way of limiting the imitability of resources or capacities - which is also common practice in the biotechnology industry - is the application of industrial property rights (e.g., patents; Peters 2008, p. 379). Therefore, a resource or capability is supposed to be imperfectly imitable in order to be a source of competitive advantage (Barney et al. 2001, p. 625).

[23] The basic idea of rare resources is that if a particular valuable resource is possessed by a large number of organizations, then each of these organizations will have the ability of exploiting that resource in the same way, thereby giving no organization a competitive advantage. However, Barney (1991) notes: "How rare a valuable firm resource must be in order to have the potential for generating a competitive advantage is a difficult question." (p. 107). In addition, the rareness of critical resources may be a temporary phenomenon, due to some limitations on how quickly they can be replicated (Peteraf/Barney 2003, p. 316).

The final requirement for a resource or capability to be a source of competitive advantage is the criterion of limited substitutability. In particular, there must be no equivalent valuable resources or capabilities that are themselves either not rare or imitable. Resources or capabilities are equivalent when they each can be exploited separately to obtain the same effect (e.g., the same proficiency in conducting R&D activities) (Barney 1991, p. 111). The existence of equivalent resources or capabilities entails that competing organizations can obtain the same effect or outcome, "but in a different way, using different resources" (Barney 1991, p. 111). If these alternative resources or capabilities were not rare or imitable, current and potential competitors would be able to obtain the effect or outcome in question, which in turn would prevent any organization from obtaining a competitive advantage over its competitors (Barney 1991, p. 111).

In sum, resource-based theory provides a theoretical framework to explain how competitive advantages can be achieved by organizations (e.g., by cooperative R&D ventures). In particular, it is assumed that an organization can be perceived as a nexus or bundle of resources and capabilities, which are characterized by a certain degree of heterogeneity (Eisenhardt/Martin 2000, p. 1105). For a resource or capability to hold the potential to generate a competitive advantage, it must be essential to the organization's effort to generate differentially greater value, it must be rare or scarce among an organization's current and potential competitors while additionally being imperfectly imitable and difficult to substitute using other resources or capabilities (Peteraf/Barney 2003, p. 316). Such critical resources or capabilities enable an organization to participate in its product market more efficiently (Barney 1991, p. 101; Peteraf/Barney 2003, p. 316). More efficiently in this context refers to the organization's ability to produce more economically and/or better satisfy end user (e.g., customer) needs (Peteraf/Barney 2003, p. 311).

To conclude, resource-based theory assumes a relationship between the available resources and skills and product competitive advantage. In particular, it can be expected that a fit between an R&D project's needs and the partners' combined resources and skills (i.e., technical fit and marketing research fit) positively affects product competitive advantage.

3.1.2 Information-processing Theory

In resource-based theory, competitive advantages are predicted to be the consequences of critical resources and capabilities an organization (e.g., a cooperative R&D project) possesses. However - and in their seminal framework on competitive superiority - Day/Wensley (1988, p. 7) note that superior resources and skills are not automatically converted into competitive advantages. The relationship between critical resources and skills and competitive advantages is supposed to be mediated by the proficiency in performing activities in the R&D process (e.g., market research, prototype testing) (Song/Parry 1997a, p. 3). This supposed relationship between possessed resources and skills, proficiency in conducting R&D activities and competitive advantages is consistent with the theoretical assumptions of information-processing theory (e.g., Tushman/Nadler 1978; Daft/Lengel 1986; Sinkula 1994; Song et al. 2005).

The information-processing view (Galbraith 1974) is a theoretical approach that tries to explain how information is related to the execution of activities and how the quality of activities can be enhanced through the processing and utilization of information (Schultz 2006, p. 40). In particular, it is suggested that the better the information-processing capabilities of an organization are matched to the information-processing needs it satisfies, the more efficiently the organization will operate (Weise 2007, p. 49). In fact, Keller (1994) found that industrial R&D project groups which closely matched their information-processing capabilities with the information-processing needs of their project were characterized by a higher level of project performance than groups lacking such a match.

From the theoretical perspective of information-processing theory, organizations are information-processing systems (Rogers et al. 1999, p. 568). Similarly, Daft/Weick (1984) conceptualize organizations as interpretation systems which scan and collect data (i.e., the process of monitoring the environment and providing environmental data), interpret that data (i.e., giving meaning to the data), and finally learn by drawing conclusions upon the interpretation (Keller 1994, p. 168). In the realm of information-processing theory, R&D activities are discrete information-processing activities aimed at

reducing uncertainty (Moenaert/Souder 1990, p. 93), whereby uncertainty is conceptualized as "the difference between the amount of information required to perform a particular task and the amount of information already possessed by the organization" (Galbraith 1973, p. 5). In particular, information-processing includes the gathering of data, the transformation of data into information, and the utilization of that information for the purpose of R&D (Egelhoff 1991, p. 342f.).

In the process of cooperative R&D projects, activities such as market research, business analysis, prototype development and trials generate data that need to be transformed into information. Information is "data endowed with relevance and purpose" (Drucker 1988, p. 46). Converting data into information requires specialized knowledge (Drucker 1988, p. 46; Gray 2000, p. 179). The capability to interpret the data, make sense of it and draw conclusions from it is a function of an individual's knowledge of the subject domain (e.g., knowledge of a specific scientific domain). The greater the knowledge an individual has of a subject domain, the better he or she will be able to grasp meaning inherent in data drawn from that domain (Cohen/Levinthal 1990, p. 128; Gray 2000, p. 179). If a cooperative R&D project lacks that knowledge, it will be unable to grasp meaning and draw conclusions from it (Gray 2000, p. 179).

Due to the complexity and interdisciplinarity of biotechnology, it is not possible for a single organization to internally unite all the necessary resources and skills (i.e., specialized knowledge) to competently execute the multitude of tasks of biotechnology R&D, which is characterized by various and highly specialized techniques (e.g., protein synthesis; OECD 2005, p. 7 ff.). Consequently, cooperative R&D projects in the biotechnology industry are formed to gain access to specialized knowledge needed to perform a particular task in R&D (Ortiz 2013, p. 281). Thus, cooperative R&D project teams are information-processing task groups of specialized individuals from different domains (Moenaert/Souder 1990, p. 91). These task group's combined knowledge enhances the cooperative R&D project's information-processing capability (i.e., the capability to interpret the data, make sense of it and draw conclusions from it) in order to match the information-processing needs inherent in complex and non-routine tasks in biotechnology R&D. Moreover, strategic management literature argues that "when solving complex, non-routine problems, groups are more

effective when composed of individuals having a variety of skills, knowledge, abilities, and perspectives" (Bantel/Jackson 1989, p. 109). The cooperation of individuals with different skills and perspectives is expected to enhance the likelihood of considering a larger set of problems as well as of alternative potential solutions (Mitroff 1982, p. 375; Bantel/Jackson 1989, p. 109). The resulting match between information-processing capabilities of a cooperative R&D project with the information-processing needs of its tasks is supposed to foster the proficient execution of various R&D activities in order to obtain a (product) competitive advantage.

In sum, information-processing theory asserts that the information-processing capabilities must fit the information-processing requirements facing an organization in order to be effective (Tushman/Nadler 1978). A lack of fit between project needs and available resources and skills implies a gap between the possessed information-processing capabilities and the information-processing capabilities required to perform particular R&D activities. A fit between project needs and available resources and skills implies a match between the possessed information-processing capabilities and the information-processing capabilities required to proficiently perform particular R&D activities in order to obtain a product competitive advantage.

In contrast to resource-based theory, information-processing theory does not automatically assume a direct link between an R&D project's critical resources and skills and competitive advantages. Instead, it is suggested that the fit of possessed resources and skills with the R&D project's needs enables the proficient execution of R&D activities which aim to develop a superior and meaningful product (i.e., product competitive advantage).

3.2 Research Model

Figure 7 presents the conceptual model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. The model is based on two fundamental notions. First and consonant with resource-based theory (e.g., Barney 1991; Peteraf 1993), competitive advantages derive from resources and skills that are rare and superior

in use, relative to others (Peteraf/Barney 2003, p. 311). Second and in the view of information-processing theory (e.g., Tushman/Nadler 1978), activities in R&D projects are discrete information-processing activities. Thus, cooperative R&D project teams are information-processing task groups of specialized individuals for the purpose of competently execute these activities (Moenaert/Souder 1990, p. 91ff.). Product competitive advantage in cooperative R&D projects between biotechnology firms and PRI is hypothesized to be the consequence of how well the partners' resources and skills are matched in order to competently execute activities that characterize such R&D projects (i.e., technical and marketing-related activities). This is in consensus with the rational plan stream of NPD research, which emphasizes that successful product development is the result of rational planning and execution (Brown/Eisenhardt 1995, p. 348ff.; Song/Montoya-Weiss 2001, p. 62ff.).

Drawing on resource-based theory and information-processing theory, the model postulates relationships among factors extant research on NPD has related to product competitive advantage. Specifically, it is proposed that a fit between an R&D project's needs and the partners' combined resources and skills (i.e., technical fit and marketing research fit) positively affects product competitive advantage (H1 - H2). The relationship between a cooperative R&D project's fit with the partners' combined resources and skills and product competitive advantage is expected to be partially mediated[24] by proficiency in the R&D process (i.e., the competent execution of various marketing and technical activities) (H3 – H8). In addition, it is also necessary to consider the specific characteristics of the biotechnology industry. Success of R&D in the biotechnology industry cannot be guaranteed per se, as it involves highly experimental research (De Luca et al. 2010, p. 308). Therefore, it is hypothesized that the presumed positive relation between the proficient execution of activities in the development process and product competitive advantage is partially mediated by fulfilling the initial R&D objectives (H9-10).

[24] Partial mediation refers to a situation in which "a portion of the effect of [the independent variable] on [the dependent variable] is mediated through [a mediator variable], whereas [the independent variable] still explains a portion of [the dependent variable] that is independent of [the mediator variable]" (Nitzl et al. 2016, p. 1856).

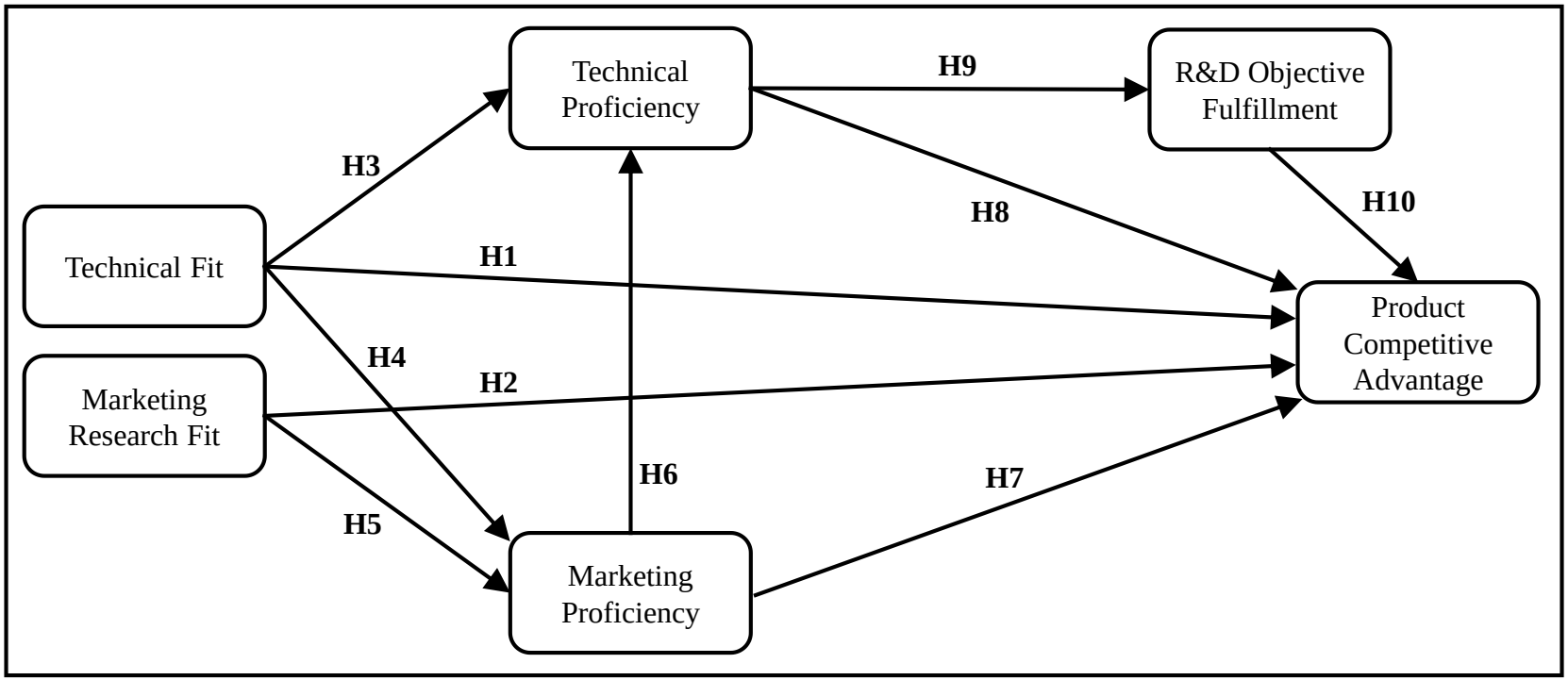

Figure 7: Research model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective

3.3 Hypotheses

R&D cooperations are "formal collaborative arrangements among organizations with the objective to co-operate on research and development activities" (Petruzzelli 2011, p. 310). Since R&D activities are getting more complex and interdisciplinary, firms and PRI cooperate in order to gain access to resources and skills they do not possess on their own (Miotti/Sachwald 2003, p. 1482). The motivation of biotechnology firms to collaborate with PRI is to gain access to leading-edge knowledge and expertise that does not exist within the internal R&D division (Ortiz 2013, p. 281 ff.). PRI often lack the resources to conduct research on a larger scale. Production capacities on an industrial scale or high-throughput technologies are provided by larger biotechnology firms. Smaller, specialized biotechnology firms contribute to collaborations by providing specific services, analyzers and proprietary methods (Ortiz 2013, p. 255 ff.). Consequently, cooperative R&D projects are to be regarded as temporary forms of organization in which the partners' complementary resources and skills are combined with the objective to create new knowledge that can be patented and/or results in a prototype (Rothaermel/Deeds 2004, p. 204; Ortiz 2013, p. 281 f.). In other words, by combining the resources and skills of biotechnology firms and PRI the anticipated outcome of the cooperation is a product (i.e., a biotechnological invention), which offers unique performance characteristics, is superior in quality and in meeting the needs of a target audience (e.g., potential investor, scientific community). Empirical studies in NPD research report that sources of such a product competitive advantage are the resources and skills available in a development project (e.g., Song/Parry 1996; Song/Parry 1997b; Harmancioglu et al. 2009).

From the theoretical view of resource-based theory, competitive advantages derive from resources and capabilities that are rare, difficult to imitate, non-substitutable and superior in use, relative to others (Peteraf/Barney 2003, p. 311; e.g., Barney 1991; Peteraf 1993; Eisenhardt/Martin 2000). In general, the term competitive advantage refers to the superior value creation of an organization (e.g., a superior product) relative to its existing and potential competitors in a (product) market (Peteraf/Barney 2003, p. 311). An organization

– as the value-creating entity – can be viewed as a nexus or bundle of resources and capabilities (Lado et al. 1992, p. 78). Resources and capabilities at a given time are those (tangible and intangible) assets that are tied to an organization (e.g., knowledge of technology; Wernerfelt 1984, p. 172). For a resource or capability to hold the potential to generate a competitive advantage, it must be essential to the organization's effort to generate differentially greater value, it must be rare or scarce among an organization's current and potential competitors while additionally being imperfectly imitable and difficult to substitute using other resources or capabilities (Barney 1991, p. 101; Peteraf/Barney 2003, p. 316).[25] Such critical resources and capabilities enable an organization to participate in its product market more efficiently (Barney 1991, p. 101; Peteraf/Barney 2003, p. 316). More efficiently in this context refers to the organization's ability to produce more economically and/or better satisfy end user (e.g., customer) needs (Peteraf/Barney 2003, p. 311).

Studies in NPD research have reported that product competitive advantage is associated with marketing-related resources and skills as well as technical resources and skills (see section 2.1.2). The focus in these studies is on fit of the development project's needs with available resources and skills, specifically in terms of fit with marketing-related and/or technical resources and skills. A positive association between adequate resources and skills and product competitive advantage can be expected because the primary criteria for selecting a partner in the biotechnology industry are scientific excellence, professional expertise as well as technical and human capacities in a specific field of research (Ortiz 2013, p. 231ff.). Biotechnology firms and PRI cooperate in order to create a fit between their resources and skills with the R&D project's needs. The criterion of scarce resources is reflected in the tacit knowledge and expertise of researchers from PRI and biotechnology firms. Tacit knowledge represents understanding

[25] The basic idea of rare resources is that if a particular valuable resource is possessed by a large number of organizations, each of these organizations will have the ability of exploiting that resource in the same way, thereby giving no organization a competitive advantage. However, Barney (1991, p. 107) notes: "How rare a valuable firm resource must be in order to have the potential for generating a competitive advantage is a difficult question." In addition, the rareness of critical resources may be a temporary phenomenon, due to some limitations on how quickly they can be replicated (Peteraf/Barney 2003, p. 316).

gained from experience and is thus bound to a person and cannot be expressed that easily to another person (Polanyi 1966, p. 4ff.). These human assets are difficult to imitate due to scarcity, specialization, and tacit knowledge (Coff 1997, p. 374). Therefore, it is hypothesized the following:

H1: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences product competitive advantage.

H2: A cooperative R&D project's fit with the partners' combined marketing research skills and resources (i.e., marketing research fit) positively influences product competitive advantage.

Product competitive advantage is argued to be the consequence of relative superiority in the resources and skills a cooperative R&D project possesses. In their seminal work on competitive advantages, Day/Wensley (1988, p. 7) note that superior resources and skills are not automatically converted into competitive advantages. The relationship between superior resources and skills and product competitive advantage is expected to be (partially) mediated by the proficiency in performing marketing (e.g., market research) and technical activities (e.g., prototype testing), which characterize the cooperative R&D project (Song/Parry 1997a, p. 3). Proficiency refers to “how well or adequately” these marketing and technical activities are executed (Song/Parry 1997a, p. 13). Empirical studies in NPD research indeed report a positive association between technical and marketing fit and proficiency in technical and marketing activities, respectively (see section 2.1.2).

From the theoretical view of information-processing theory (e.g., Tushman/Nadler 1978; Daft/Lengel 1986; Sinkula 1994; Song et al. 2005), R&D activities are discrete information-processing activities aimed at reducing uncertainty (Moenaert/Souder 1990, p. 93). Uncertainty is “the difference between

the amount of information required to perform a particular task and the amount of information already possessed by the organization" (Galbraith 1973, p. 5). In particular, information-processing includes the gathering of data, the transformation of data into information, and the utilization of that information for the purpose of R&D (Egelhoff 1991, p. 342f.).

In the process of cooperative R&D projects, activities such as market research, business analysis, prototype development and trials generate data that need to be transformed into information. Information is "data endowed with relevance and purpose" (Drucker 1988, p. 46). Converting data into information requires specialized knowledge (Drucker 1988, p. 46; Gray 2000, p. 179). The capability to interpret the data, make sense of it and draw conclusions from it is a function of an individual's knowledge of the subject domain (e.g., knowledge of a specific scientific domain). The greater the knowledge an individual has of a subject domain, the better he or she will be able to grasp meaning inherent in data drawn from that domain (Cohen/Levinthal 1990, p. 128; Gray 2000, p. 179). If a cooperative R&D project lacks that knowledge, it will be unable to grasp meaning and draw conclusions from it (Gray 2000, p. 179).

Due to the complexity and interdisciplinarity of biotechnology, it is not possible for a single organization to internally unite all the necessary resources and skills (i.e., specialized knowledge) to competently execute the multitude of tasks of biotechnology R&D, which is characterized by various and highly specialized techniques (e.g., protein synthesis; OECD 2005, p. 7 ff.). Consequently, cooperative R&D projects in the biotechnology industry are formed to gain access to specialized knowledge needed to perform a particular task in R&D (Ortiz 2013, p. 281). Cooperative R&D project teams are information-processing task groups of specialized individuals from different domains (Moenaert/Souder 1990, p. 91). In addition, strategic management literature argues that "when solving complex, non-routine problems, groups are more effective when composed of individuals having a variety of skills, knowledge, abilities, and perspectives" (Bantel/Jackson 1989, p. 109). The cooperation of individuals with different skills and perspectives is expected to enhance the likelihood of considering a larger set of problems as well as of alternative potential solutions (Mitroff 1982, p. 375; Bantel/Jackson 1989, p. 109).

In sum, information-processing theory asserts that the information-processing capabilities[26] must fit the information-processing requirements facing an organization in order to be effective (Tushman/Nadler 1978). A lack of fit between project needs and available resources and skills implies a gap between the possessed information-processing capabilities and the information-processing capabilities required to perform particular R&D activities. A fit between project needs and available resources and skills implies a match between the possessed information-processing capabilities and the information-processing capabilities required to perform particular R&D activities. Therefore, it is hypothesized the following:[27]

H3: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences technical proficiency.

H4: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences marketing proficiency.

[26] Here, information-processing capability is understood or represented in terms of the cognitive abilities of organizational members (either individually or collectively) to gather and interpret data, as well as utilizing the resulting information (Egelhoff 1991, p. 346). For a discussion about the different conceptualizations of information-processing capability, see Egelhoff (1991, p. 346).

[27] Please note that it is not expected that a cooperative R&D project's fit with the partners' combined marketing research skills and resources (i.e., market research fit) is positively related to technical proficiency. The rationale is that expertise in marketing research is not regarded as necessary for the proficient execution of development activities (e.g., prototype testing). On the contrary, it is expected that a cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) is positively related to marketing proficiency. The underlying notion is that scientific expertise may contribute to the interpretation of marketing data, which enables a proficient execution of the various marketing activities. For instance, scientific expertise in a research field may facilitate the evaluation of competitive technologies and products of that particular domain.

H5: A cooperative R&D project's fit with the partners' combined marketing research skills and resources (i.e., market research fit) positively influences marketing proficiency.

It is argued that the more the cooperative R&D project has closed the gap between the required and possessed information-processing capacities, the better will be its execution of marketing and technical activities. The proficient execution of marketing and technical activities is expected to leverage product competitive advantage because these activities aim at developing a product that is superior to competitive offerings and meaningful to end users (e.g., potential customers). This is in accordance with empirical studies in NPD research reporting a positive association between proficiency in NPD activities and product competitive advantage (see section 2.1.3).

Proficiency in marketing activities refers to how well marketing-related activities are conducted during a particular cooperative R&D project. Marketing-related activities include an initial evaluation of the R&D project, determining the desired features of the biotechnological product, identifying potential markets and trends for the biotechnological product, conducting a market study, appraising existing and potential competitors and their biotechnological inventions, as well as identifying characteristics that would differentiate the product and contribute to its sale (Song/Parry 1999). Those marketing-related activities provide data, which are transformed into information that guide the direction of the development process. This information can be integrated into the development process by matching product attributes and functionalities with the needs of end users and in compliance with competitive offerings. They enable researchers and managers in cooperative R&D projects to check whether the product attributes and features are indeed superior to competitive products, as well as beneficial for end users. Information on end users' needs may also initiate the development of a specific product (Rijsdijk et al. 2011, p. 37). Therefore, marketing activities represent predevelopment activities, whose competent execution provide the basis for proficiently conducting the actual development activities (i.e., technical activities), as well as the efforts that enable a cooperative R&D project to position

the new product as superior to competing offerings within a given market and as meaningful to potential users. Hence, it is hypothesized the following:

H6: Marketing proficiency positively influences technical proficiency.

H7: Marketing proficiency positively influences product competitive advantage.

Proficiency in technical activities refers to how well technical-related activities are conducted during a particular cooperative R&D project. Technical-related activities include evaluating the feasibility of developing and manufacturing a product with the desired features, developing the product according to the desired features, evaluating laboratory tests to determine the actual product features, executing prototype testing, elaborating a detailed plan for the industrial production of the product as well as continuously considering costs and quality of the product (Song/Parry 1999). Proficiency in technical activities represents the efforts to develop a product with superior quality, unique attributes and performance characteristics. Therefore, it is hypothesized the following:

H8: Technical proficiency positively influences product competitive advantage.

When considering the positive relationship between technical proficiency and product competitive advantage, it is also necessary to take into account the specific characteristics of the biotechnology industry. Success of R&D in the biotechnology industry cannot be guaranteed per se, as it concerns highly experimental research (De Luca et al. 2010, p. 308). For instance, the probability that a discovered molecule will successfully pass through the entire development process is very low. Of every 10,000 compounds tested, only 250 enter preclinical testing. Only 2% of these so-called lead candidates make it into clinical trials

(Honek 2017, p. 6). These figures illustrate that R&D projects in the biotechnology industry inherent uncertainty with regard to their potential outcome (Rothaermel/Deeds 2004 p. 208f.). Therefore, it is expected that the positive impact of technical proficiency on product competitive advantage is partially mediated by the fulfillment of the initial R&D objectives.

The proficient execution of technical activities (e.g., prototype testing) generates data that is interpreted and drawn conclusions from (Egelhoff 1991, p. 342f.). Such information serves as input for the iterative process of technical R&D activities. It is expected that the more proficient technical activities are conducted, the more valuable information will be obtained that will support the product development process and thus the fulfillment of the R&D objective. Under the notion of specifying the research goal based on user preferences, market trends and a clear understanding of "appeal" characteristics that would differentiate the product, the fulfillment of the R&D objective should be closely connected to achieving a product competitive advantage (i.e., a product that is superior to competitive offerings and meaningful to target users). Therefore, it is hypothesized the following:

H9: Technical proficiency positively influences R&D objective fulfillment.

H10: R&D objective fulfillment positively influences product competitive advantage.

To conclude, Figure 8 gives a summary of the hypotheses of this thesis. The results of the empirical analysis of the hypotheses developed in this section will be discussed in the following section.

H1: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences product competitive advantage.

H2: A cooperative R&D project's fit with the partners' combined marketing research skills and resources (i.e., marketing research fit) positively influences product competitive advantage.

H3: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences technical proficiency.

H4: A cooperative R&D project's fit with the partners' combined technical skills and resources (i.e., technical fit) positively influences marketing proficiency.

H5: A cooperative R&D project's fit with the partners' combined marketing research skills and resources (i.e., market research fit) positively influences marketing proficiency.

H6: Marketing proficiency positively influences technical proficiency.

H7: Marketing proficiency positively influences product competitive advantage.

H8: Technical proficiency positively influences product competitive advantage.

H9: Technical proficiency positively influences R&D objective fulfillment.

H10: R&D objective fulfillment positively influences product competitive advantage.

Figure 8: Summary of hypotheses H1 through H10

4 Empirical Analysis of the Research Model

The objective of the empirical analysis is to evaluate the model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. The overall research design to pursue this objective can be summarized as follows: In the previous sections, the hypotheses were derived by drawing from resource-based theory (e.g., Barney 1991; Peteraf 1993), information-processing theory (e.g., Tushman/Nadler 1978), as well as extant literature on NPD (e.g., Song/Parry 1996; Harmancioglu et al. 2009). An empirically testable model was developed, which illustrates the contributing factors, as well as their interrelationships, for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. The hypotheses about the relationships between the factors that contribute to the achievement of a product competitive advantage (i.e., technical fit, marketing research fit, marketing proficiency, technical proficiency, R&D objective fulfillment) are the basis for the empirical analysis of the research model.

In order to conduct the empirical analysis of the research model, Section 4.1 defines cooperative R&D projects between biotechnology firms and PRI as the objects of study. The methodology of data collection for the empirical analysis of the research model is presented in Section 4.2. The hypotheses about the relationships between the factors that contribute to the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI are tested via the quantitative research methodology of a survey. Section 4.3 illustrates the operationalization of the variables of the research model and Section 4.4 describes the structure of the questionnaire. Subsequently, the sample is described in Section 4.5 and then analyzed descriptively in Section 4.6. The statistical analysis technique of structural equation modeling is introduced in Section 4.7 and the corresponding evaluation of the results is presented in Section 4.8. The evaluation closes with a summary of the results. Figure 9 illustrates the structure of the empirical analysis.

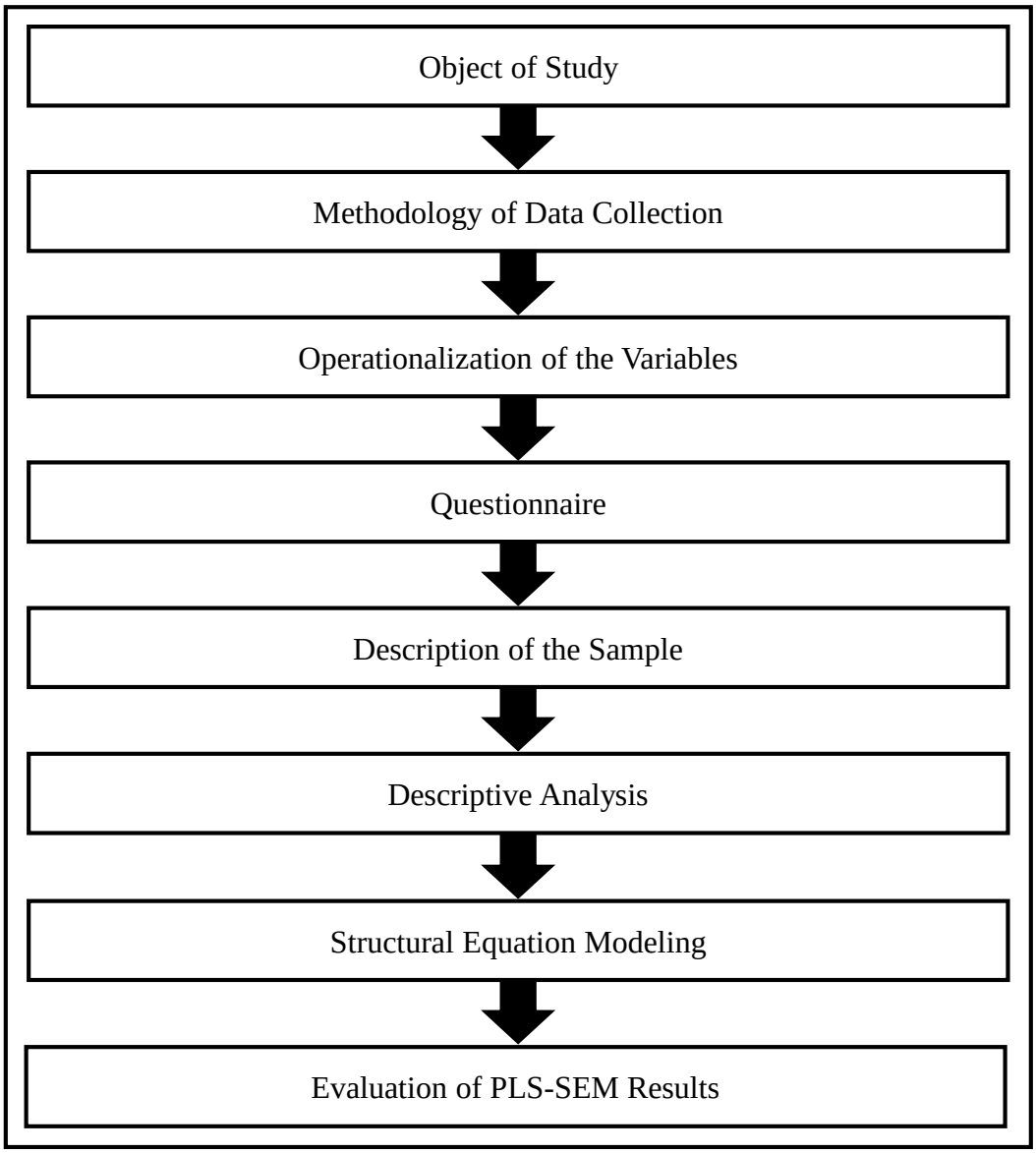

Figure 9: Structure of the empirical analysis

4.1 Object of Study

Cooperative R&D projects between biotechnology firms and PRI are the objects of study of this thesis. In this thesis, cooperative R&D projects are defined as formal collaborative arrangements between at least one biotechnology firm and at least one PRI with the objective to cooperate on R&D activities (Petruzzelli 2011, p. 310). Cooperative R&D projects are representative of R&D ventures in knowledge-intensive industries such as the biotechnology industry, since small and medium-sized enterprises need to cooperate in R&D with PRI to cope with their strong dependence on scientific expertise (Ortiz 2013, p. 281 ff.). The biotechnology industry is characterized by complexity and interdisciplinarity,

which hardly makes it possible for a single organization to internally unite all the necessary competencies and resources to master the multitude of required and highly specialized techniques of biotechnology (e.g., protein synthesis; OECD 2005, p. 7 ff.). To close the gap between existing and required expertise and resources, cooperative R&D projects between biotechnology firms and PRI are initiated in order to gain access to specialized knowledge that is not available in-house (Ortiz 2013, p. 281).

Such cooperative R&D projects constitute temporary forms of organization in which the complementary resources and skills of the partners are combined with the objective of creating new knowledge that can be patented and/or results in a prototype (Rothaermel/Deeds 2004, p. 204; Ortiz 2013, p. 281f.). The anticipated outcome of cooperative R&D projects between biotechnology firms and PRI is a product (i.e., a biotechnological invention), which has the potential to raise money for the subsequent costly and time consuming (clinical) testing efforts until a biotechnological invention results in a marketable product (e.g., pharmaceutical drug) (Rothaermel/Deeds 2004, p. 204; Schüler 2016, p. 167 ff.).

4.2 Methodology of Data Collection

The research question of this thesis involves the investigation of factors affecting product competitive advantage in cooperative R&D ventures between biotechnology firms and PRI at the project level, with the purpose of providing insights into how cooperative R&D projects between biotechnology firms and PRI should be designed and executed to support the achievement of a product competitive advantage. In order to achieve this objective, survey research was selected as methodology of data collection as it allows for a large-scale test of the research hypotheses and has been successfully applied in research on NPD (e.g., Harmancioglu et al. 2009) and studies on R&D cooperations between firms and PRI (e.g., Mora-Valentin et al. 2004). In particular, structural equation modeling (Chin 1998b) was identified to be the most advantageous approach, since it allows to capture the interrelationships among determinants and to assess in which ways factors contribute to achieving a product competitive advantage (Hair et al. 2016). Data were collected using an online survey.

Since the focus of this thesis is on cooperative R&D projects between biotechnology firms and PRI, data were collected from both types of partners. This is in consensus with Mora-Valentin et al. (2004, p. 24), who argue that most studies on the topic analyze information solely about one type of partner, though both types of partners must be included for a comprehensive and detailed analysis. The sampling frame was drawn from the database of the Internet portal biotechnology.de, which was initiated by the German Federal Ministry of Education and Research (BMBF) in 2006. The database offers information on German biotechnology firms and PRI active in the field of biotechnology. Each individual website of the listed biotechnology firms and PRI was visited for the purpose of collecting personal email addresses[28] of potential key informants (i.e., experts that are knowledgeable of cooperative R&D project between at least one biotechnology firm and one PRI). Each potential key informant was asked to participate in an online questionnaire regarding a cooperative R&D project between at least one biotechnology firm and one PRI he or she is knowledgeable of.

This approach of questioning key informants is in correspondence with extant literature in the domain of NPD (e.g., Li/Calantone 1998; Langerak et al. 2004; Veldhuizen et al. 2006; Harmancioglu et al. 2009; McNally et al. 2010; Rijsdijk et al. 2011; Slotegraaf/Atuahene-Gima 2011). Questioning key informants is a widely used approach in the course of quantitative, large-scale investigations, which must cope with a lack of archival data with regard to the phenomena under investigation (Kumar et al. 1993, p. 1633). Informants do not need to be representatives of the members of a studied entity (i.e., cooperative R&D project between biotechnology firms and PRI). Rather, they are selected on the basis of their knowledge of the issue being studied (Kumar et al. 1993, p. 1634). In addition, and suggested by Kumar et al. (1993), as well as regularly applied in NPD literature (Li/Calantone 1998; Langerak et al. 2004; Veldhuizen et al. 2006), a self-assessment of respondents' knowledgeability was adopted. Respondents were asked how knowledgeable they are of the cooperative R&D project between at least one biotechnology firm and one PRI. Evidence of

[28] Personal email address refers to an email address which contains the name of the potential respondent.

knowledgeability was assessed on a seven-point Likert scale (anchored at "not knowledgeable at all"/"totally knowledgeable") (Li/Calantone 1998, p. 20). This procedure allowed to eliminate questionnaires from the examination due to informants' inadequate knowledge (Heide/John 1990, p. 30; Heide/Miner 1992, p. 273).[29]

4.3 Operationalization of the Variables

This section presents the operationalization of the constructs of the research model (i.e., product competitive advantage, technical fit, marketing research fit, marketing proficiency, technical proficiency, and R&D objective fulfillment). The measurement scales described below have been adapted from existing scales from the NPD literature to the context of cooperative R&D projects between biotechnology firms and PRI.[30]

Product competitive advantage is a theoretical construct that is composed of two components: product superiority and product meaningfulness (Rijsdijk et al. 2011, p. 33ff.). Product superiority refers to the extent to which a product offers unique performance characteristics, is superior in quality and in meeting the needs of a target audience (e.g., potential investor, scientific community) (Song/Parry 1996, p. 427; Song/Parry 1999, p. 673; Harmancioglu et al. 2009, p. 274; McNally et al. 2010, p. 1000). Product meaningfulness concerns the values, benefits, and advantages target end users receive from using the product (Rijsdijk et al. 2011, p. 33). The rationale of conceptualizing product competitive advantage as a composite of both product superiority and product meaningfulness

[29] See Section 4.5 “Description of the Sample” for more information on the self-assessment of respondents’ knowledgeability.

[30] This adaption involved the rewording and modification of items which have been originally developed to fit into the context of industrial NPD but may lead to confusion if not translated according to the characteristics of the biotechnology industry. Please consider the following item from the NPD literature (Song/Parry 1999) as an example: “Initial Screening of the product idea - the first review of the venture.” In the realm of biotechnology, screening may refer to methods for the discovery of bioactive substances (Devlin 1997). Therefore, the item had to be reworded and modified to not be misunderstood by stakeholders in the biotechnology industry: “An initial evaluation of the R&D project based on criteria relevant to success (e.g., feasibility, project scope, exploitation potential).” However, the basic meaning of the items was not altered.

is that a product needs to be superior as well as meaningful in order to gain an advantage over competitive offerings as a major prerequisite of product success (Cooper 1979a, b; Cooper/Kleinschmidt 1987; Zirger/Maidique 1990; Cooper/Kleinschmidt 1993; Parry/Song 1994; Song/Parry 1996; Song/Parry 1997b; Langerak et al. 2004; Nakata et al. 2006; Veldhuizen et al. 2006; Li/Calantone 1998; McNally et al. 2010). For instance, a product may outperform competing products (e.g., in terms of quality), but it still does not have any meaning for the user, since it is superior in terms of features that have no significance for the user (Rijsdijk et al. 2011, p. 36). Being a construct composed of two components, product competitive advantage was operationalized as a higher-order construct that is jointly formed by two lower-order constructs (i.e., product superiority and product meaningfulness) (Chin 2010, p. 665f.; Hair et al. 2016, p. 281ff.). Product superiority was measured by three items adapted from Harmancioglu et al. (2009). These items concern a product's uniqueness and performance characteristics, as well as superiority in terms of quality and meeting user needs. Product meaningfulness was measured by three items with regard to benefits, value, and advantages of the product to the user, which were adapted from Rijsdijk et al. (2011).

Figure 10 illustrates the composition of the higher-order construct of product competitive advantage. The depicted operationalization assumes that each of the two lower-level constructs (i.e., product meaningfulness and product superiority) constitutes a certain aspect of the higher-order construct's domain. Taken both these lower-order constructs together, they determine the meaning of product competitive advantage (Rijsdijk et al. 2011, p. 33ff.). Therefore, the direction of causality is from the lower-order constructs to the higher-order construct of product competitive advantage. In addition, the composition of both lower-order constructs is illustrated. First, it is assumed that the indicators PM_1, PM_2, and PM_3 represent the manifestation of the lower-order construct of product meaningfulness. Second, the operationalization in Figure 10 is based on the idea that the indicators PS_1, PS_2, and PS_3 represent the manifestation of the lower-order construct of product superiority. Therefore, the direction of causality is from the lower-order constructs to their respective indicators. In sum,

product competitive advantage is operationalized as a formatively measured higher-order construct (see Section 4.7 for further information).

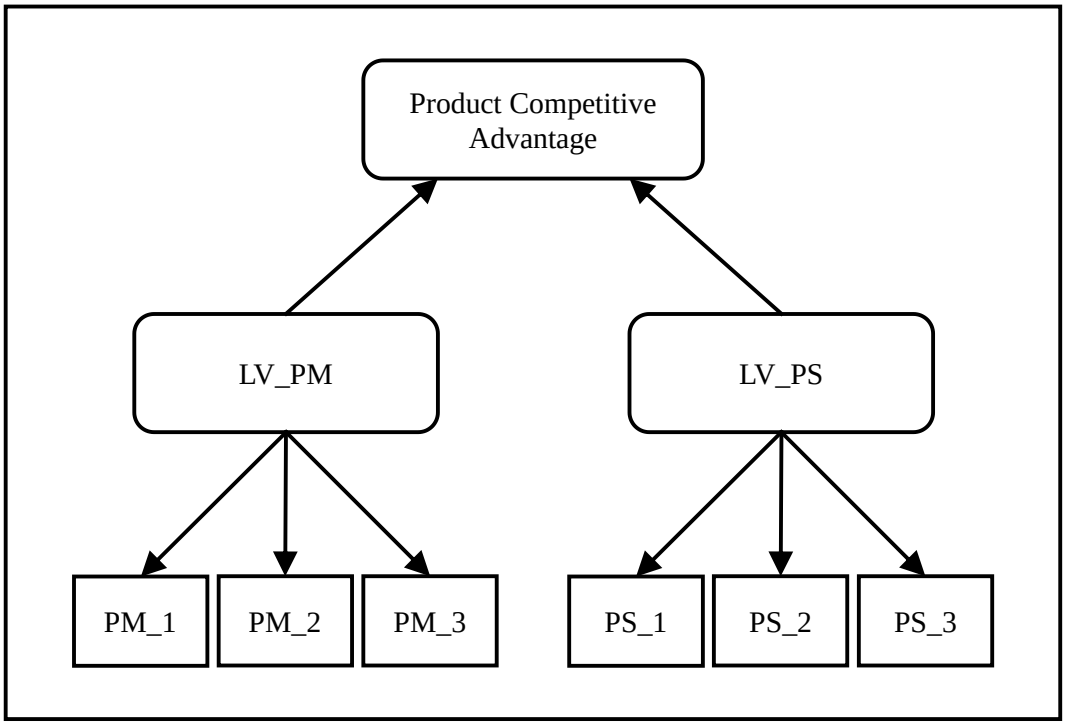

Figure 10: Operationalization of product competitive advantage

Technical fit refers to the adequacy of the technical capabilities and assets possessed by a cooperative R&D project between biotechnology firms and PRI. Categories of technical capabilities include the scientific expertise and the know-how regarding industrial production available in a cooperative R&D project between a biotechnology firm and a PRI (Harmancioglu et al. 2009). Of actual importance is how well the project partner's scientific expertise and know-how regarding industrial production match the requirements of the cooperative R&D project (Song/Parry 1997a, p. 7). Furthermore, the construct of technical fit covers how well the partners' combined resources for R&D and industrial production fit with the cooperative R&D project requirements. The concern here is not on the magnitude of R&D and industrial production resources but rather on the appropriateness of the resources given the cooperative R&D project needs (Song/Parry 1997a, p. 7). Technical fit was measured by four items adapted from Song/Parry (1997a). Figure 11 illustrates the composition of the construct of technical fit. The depicted operationalization assumes that the indicators (i.e., TF_1, TF_2; TF_3; TF_4) represent the manifestation of the construct (i.e.,

technical fit). Therefore, the direction of causality is from the construct of technical fit to the indicators. In sum, technical fit is operationalized as a reflectively measured construct (see Section 4.7 for further information).

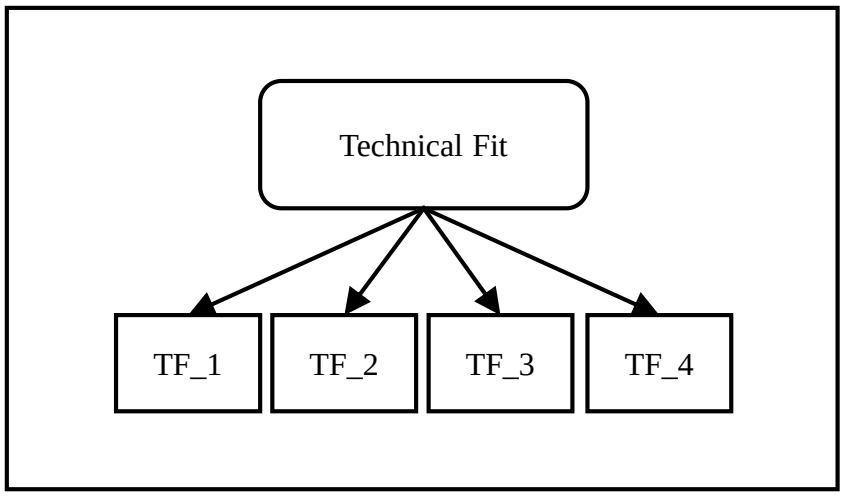

Figure 11: Operationalization of technical fit

Marketing research fit refers to the adequacy of the marketing research capabilities and assets possessed by a cooperative R&D project between biotechnology firms and PRI. Marketing research capabilities are complex bundles of experience and knowledge that enable cooperative R&D projects and its members to coordinate activities and make use of their assets (Day 1994). Of particular importance is how well the project partner's marketing capabilities and expertise match the requirements of the cooperative R&D project (Song et al. 1997a, p. 58). In addition, the construct of marketing research fit captures how well the partners' combined resources for marketing research fit with the cooperative R&D project requirements. The focus here is not on the magnitude of marketing research resources but rather on the appropriateness of the resources given the cooperative R&D project needs (Song et al. 1997a, p. 58). Marketing research fit was measured by two items adapted from Song/Parry (1997a).

Figure 12 illustrates the composition of the construct of marketing research fit. The depicted operationalization assumes that the indicators (i.e., MRF_1, MRF_2) represent the manifestation of the construct (i.e., marketing research fit). Therefore, the direction of causality is from the construct of marketing research fit to the indicators. In sum, marketing research fit is operationalized as a reflectively measured construct (see Section 4.7 for further information).

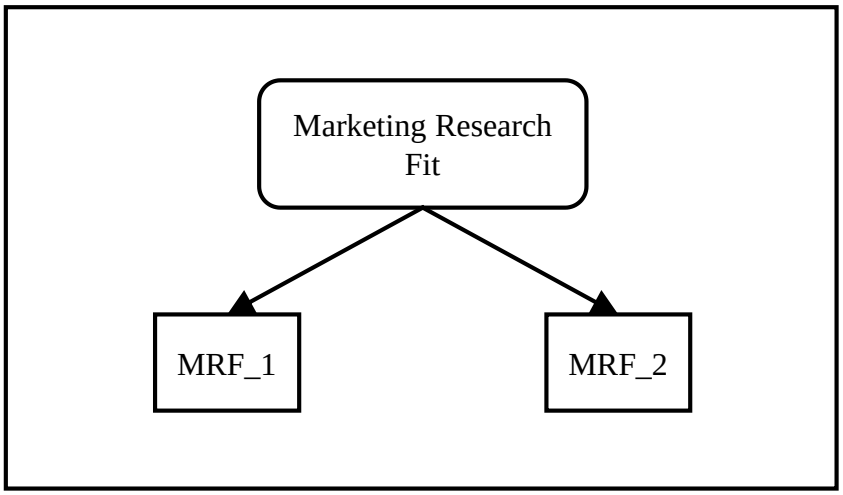

Figure 12: Operationalization of marketing research fit

Proficiency in the R&D process concerns the competent execution of various marketing and technical activities (Song/Parry 1997a, p. 13). Marketing proficiency (i.e., proficiency in marketing activities) refers to how well marketing-related activities are conducted during a particular cooperative R&D project. Marketing-related activities include an initial evaluation of the R&D project, determining the desired features of the biotechnological product, identifying potential markets and trends for the biotechnological product, conducting a market study, appraising existing and potential competitors and their biotechnological inventions, as well as identifying characteristics that would differentiate the product and contribute to its sale (Song/Parry 1999). These activities were measured by six items adapted from Song/Parry (1999).

Figure 13 illustrates the composition of the construct of marketing proficiency. The depicted operationalization assumes that each indicator constitutes a certain aspect of the construct's domain. Taken all indicators together (i.e., MP_1, MP_2, MP_3, MP_4, MP_5, and MP_6), they determine the meaning of marketing proficiency (Hair et al. 2016, p. 47). Therefore, the direction of causality is from the indicators to the construct of marketing proficiency. In sum, marketing proficiency is operationalized as a formatively measured construct (see Section 4.7 for further information).

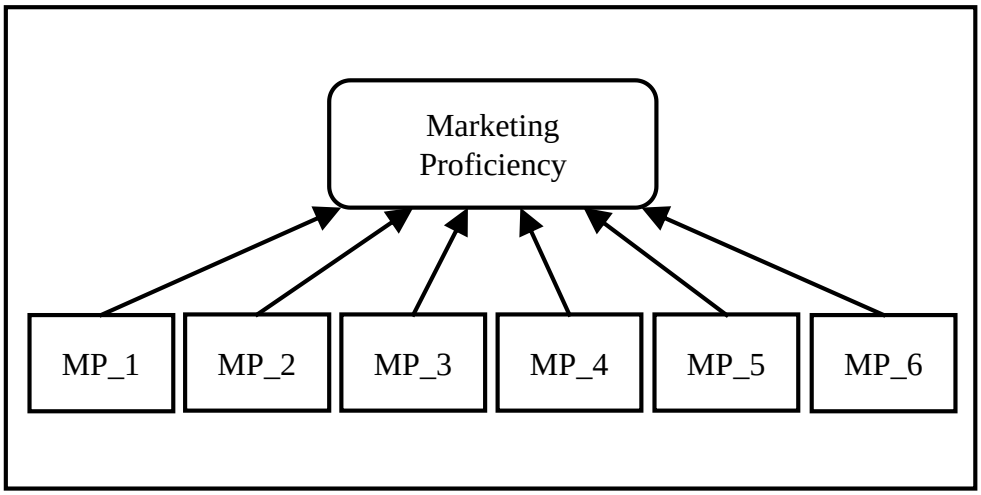

Figure 13: Operationalization of marketing proficiency

Technical proficiency (i.e., proficiency in technical activities) refers to how well technical-related activities are conducted during a particular cooperative R&D project. Technical-related activities include evaluating the feasibility of developing and manufacturing a product with the desired features, developing the product according to the desired features, evaluating laboratory tests to determine the actual product features, executing prototype testing, elaborating a detailed plan for the industrial production of the product as well as continuously considering costs and quality of the product (Song/Parry 1999). These activities were measured by six items adapted from Song/Parry (1999).

Figure 14 illustrates the composition of the construct of technical proficiency. The depicted operationalization assumes that each indicator constitutes a certain aspect of the construct's domain. Taken all indicators together (i.e., TP_1, TP_2, TP_3, TP_4, TP_5, and TP_6), they determine the meaning of technical proficiency (Hair et al. 2016, p. 47). Therefore, the direction of causality is from the indicators to the construct of technical proficiency. In sum, technical proficiency is operationalized as a formatively measured construct (see Section 4.7 for further information).

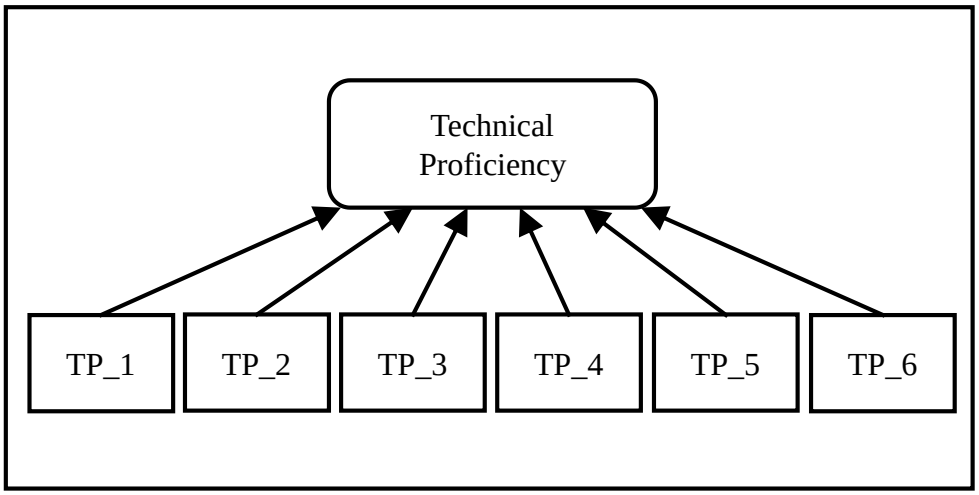

Figure 14: Operationalization of technical proficiency

R&D objective fulfillment refers to the achievement of the pursued objectives, which were defined in the early stages of the cooperative R&D project between the biotechnology firm and the PRI. The construct was measured by three items taken from from Mora-Valentin et al. 2004.

Figure 15 illustrates the composition of the construct of R&D objective fulfillment. The depicted operationalization assumes that the indicators (i.e., OF_1, OF_2; OF_3) represent the manifestation of the construct (i.e., R&D objective fulfillment). Therefore, the direction of causality is from the construct of R&D objective fulfillment to the indicators. In sum, R&D objective fulfillment is operationalized as a reflectively measured construct (see Section 4.7 for further information).

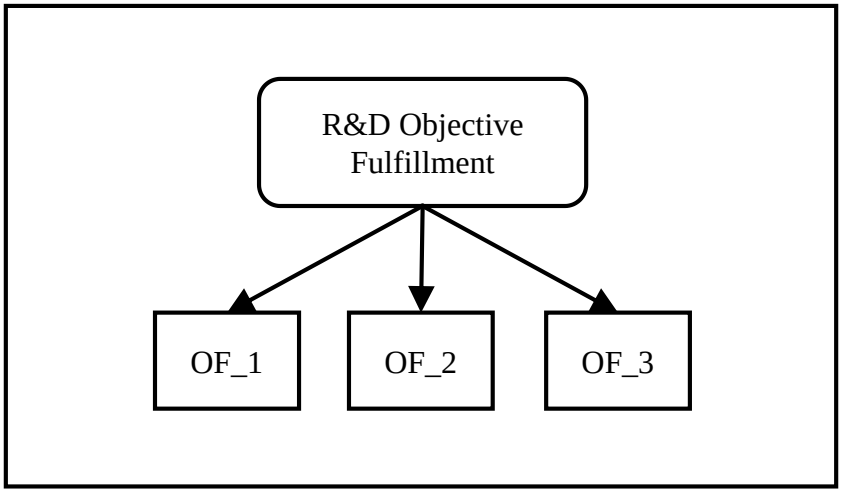

Figure 15: Operationalization of R&D objective fulfillment

Tables 23 to 27 summarize the operationalization of the variables that constitute the research model.

Table 23: Summary of the operationalization of the variables (I)

Variable	Indicator	Item Formulation	Selected Sources
Technical fit	TF_1	The scientific expertise available in the project was more than adequate for this R&D project.*	Item developed by Cooper (1979a) and used by Calantone et al. (1996), Song et al. (1997b), Song/Parry (1997a,b), Souder et al. (1997), Song/Parry (1999), Harmancioglu et al. (2009)
	TF_2	The resources available in the project for R&D (e.g., technical equipment) were more than adequate for this R&D project.*	Item developed by Cooper (1979a) and used by Calantone et al. (1996), Song et al. (1997b), Song/Parry (1997a,b), Song/Parry (1999), Harmancioglu et al. (2009)
	TF_3	The know-how available in the project for industrial production was more than adequate for this R&D project.*	Item developed by Cooper (1979a) and used by Song et al. (1997b), Song/Parry (1997a), Souder et al. (1997), Harmancioglu et al. (2009)
	TF_4	The resources available in the project for industrial production were more than adequate for this R&D project.*	Item developed by Cooper (1979a, b) and used by Song/Parry (1997a)
Marketing research fit	MRF_1	The know-how available in the project for conducting marketing research (e.g., for analyzing market potential) was more than adequate for this R&D project.*	Item developed by Cooper (1979a) and used by Calantone et al. (1996), Song et al. (1997a, b), Song/Parry (1997a), Souder et al. (1997), Song/Parry (1999), Harmancioglu et al. (2009)
	MRF_2	The resources available in the project for conducting marketing research (e.g., financial resources) were more than adequate for this R&D project.*	Item developed by Cooper (1979a, b) and used by Song et al. (1997a), Song/Parry (1997a), Song/Parry (1999), Harmancioglu et al. (2009)
Note: * Item reworded or modified to fit in the context of cooperative R&D projects between biotechnology firms and PRI.			

Table 24: Summary of the operationalization of the variables (II)

Variable	Indicator	Item Formulation	Selected Sources
Marketing proficiency	MP_1	An initial evaluation of the R&D project based on criteria relevant to success (e.g., feasibility, project scope, exploitation potential) has been done more than adequately.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Song/Parry (1996), Song/Parry (1997a), Song/Parry (1999), Harmancioglu et al. (2009)
	MP_2	A determination of desirable features of the biotechnological material or process under development has been done more than adequately.*	Item developed by Song/Parry (1996) and used by Song/Parry (1997a), Song/Parry (1999)
	MP_3	An identification of potential markets and their trends for the biotechnological material or process has been done more than adequately.*	Item developed by Song/Parry (1996) and used by Song et al. (1997a), Song/Parry (1997a, b), Song/Parry (1999)
	MP_4	Conducting a market study: A detailed analysis of market potential, preferences of potential users, etc. has been done more than adequately.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Calantone et al. (1996), Song/Parry (1996), Song et al. (1997b), Song/Parry (1997a, b), Souder et al. (1997), Song/Parry (1999), Bstieler (2005), Harmancioglu et al. (2009)
	MP_5	An appraisal of existing and potential competitors and their biotechnological inventions (materials or processes) has been done more than adequately.*	Item developed by Song/Parry (1996) and used by Song et al. (1997a), Song/Parry (1997a, b); Song/Parry (1999)
	MP_6	An identification of characteristics that would differentiate the biotechnological material or process and contribute to its sale has been done more than adequately.*	Item developed by Song/Parry (1997a, b) and used by Song/Parry (1999)
Note: * Item reworded or modified to fit in the context of cooperative R&D projects between biotechnology firms and PRI.			

Table 25: Summary of the operationalization of the variables (III)

Variable	Indicator	Item Formulation	Selected Sources
Technical proficiency	TP_1	An evaluation of the feasibility of developing and manufacturing a biotechnological material or process with the desired features has been done more than adequately.*	Item developed by Song/Parry (1999)
	TP_2	The development of the biotechnological material or process according to the desired features has been done more than adequately.*	Item developed by Song/Parry (1996) and used by Song/Parry (1997a, b), Song/Parry (1999)
	TP_3	An evaluation of laboratory tests to determine the actual features of the biotechnological material or process has been done more than adequately.*	Item developed by Song/Parry (1996) and used by Song/Parry (1997a, b), Song/Parry (1999)
	TP_4	Tests on prototypes of the biotechnological material or process have been carried out more than adequately.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Calantone et al. (1996), Song/Parry (1996), Song/Parry (1997a, b), Souder et al. (1997), Song/Parry (1999), Bstieler (2005), Millson/Wilemon (2008)
	TP_5	An elaboration of a detailed plan for the industrial production of the material or for the industrial application of the process has been done more than adequately.*	Item developed by Song/Parry (1997a) and used by Song/Parry (1999)
	TP_6	The consideration of the costs and quality of the biotechnological material or process has been done more than adequately throughout the entire R&D project.*	Item developed by Song/Parry (1997a, b) and used by Song/Parry (1999)
Note: * Item reworded or modified to fit in the context of cooperative R&D projects between biotechnology firms and PRI.			

Table 26: Summary of the operationalization of the variables (IV)

Variable	Indicator	Item Formulation	Selected Sources
R&D objective fulfillment	OF_1	We are satisfied with the project results.*	Item developed by Mora-Valentin et al. (2004)
	OF_2	The project results have fulfilled the initial expectations.*	Item developed by Mora-Valentin et al. (2004)
	OF_3	The project has provided satisfactory results for all project partners involved.*	Item developed by Mora-Valentin et al. (2004)
Product competitive advantage (higher-order construct)	LV_PM (lower-order-construct) (PM_1 – PM_3)	The biotechnological material or process is of great benefit to the user.*	Item developed by Rijsdijk et al. (2011)
		The biotechnological material or process is of great value to the user.*	Item developed by Rijsdijk et al. (2011)
		The biotechnological material or process has many advantages.*	Item developed by Rijsdijk et al. (2011)
	LV_PS (lower-order-construct) (PS_01 – PS_03)	The developed material or process has unique features or performance characteristics that are not available from biotechnological inventions of the competition.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Cooper/Kleinschmidt (1993), Song/Parry (1996), Song/Parry (1997a, b), Song/Parry (1999), Langerak et al. (2004), Nakata et al. (2006), Veldhuizen et al. (2006), Harmancioglu et al. (2009), McNally et al. (2010), Slotegraaf/Atuahene-Gima (2011)
		The developed material or process is superior to competing biotechnological inventions in terms of meeting the needs of users.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Cooper/Kleinschmidt (1993), Song/Parry (1996), Song/Parry (1997a, b), Song/Parry (1999), Langerak et al. (2004), Nakata et al. (2006), Veldhuizen et al. (2006), Harmancioglu et al. (2009), McNally et al. (2010), Rijsdijk et al. (2011)
Note: * Item reworded or modified to fit in the context of cooperative R&D projects between biotechnology firms and PRI.			

Table 27: Summary of the operationalization of the variables (V)

Variable	Indicator	Item Formulation	Selected Sources
Product competitive advantage (higher-order construct) (continued)	LV_PS (lower-order-construct) (PS_01 – PS_03) (continued)	The quality of the developed material or process is - however quality is defined by the user - superior to competing biotechnological inventions.*	Item developed by Cooper (1979a, b) and used by Cooper/Kleinschmidt (1987), Cooper/Kleinschmidt (1993), Song/Parry (1996), Song/Parry (1997a, b), Song/Parry (1999), Langerak et al. (2004), Nakata et al. (2006), Veldhuizen et al. (2006), Harmancioglu et al. (2009), McNally et al. (2010), Slotegraaf/Atuahene-Gima (2011)
Note: * Item reworded or modified to fit in the context of cooperative R&D projects between biotechnology firms and PRI.			

4.4 Questionnaire

After the variables had been operationalized, the questionnaire was developed by means of the respective items. The questionnaire was divided into six parts:

The first part included a brief introduction to the subject of the study. Afterward, the respondents were assured that all information they provide serves purely scientific purposes and will be treated strictly confidential, as well as anonymously. In addition, respondents were asked to consider an R&D project between at least one biotechnology firm and at least one research institution (university and/or non-university research institution) when answering the questionnaire. In particular, participants were advised that all answers should refer to an R&D project they had been involved in and which was completed within the last five years.

The second part included statements[31] regarding the theoretical constructs of marketing and technical proficiency. These statements involved marketing and technical activities that are frequently parts of an R&D process. Respondents were

[31] Statements represent the items used to measure the constructs, see section 4.3.

asked how well or adequately these activities have been executed in the cooperative R&D projects they were reporting. Participants were instructed to indicate the degree of their agreement with the statements by selecting a number between 1 (“don’t agree at all”) and 7 (“totally agree”) on a scale below each statement. Numbers between 1 and 7 corresponded to different degrees of agreement.

The third part included statements regarding the theoretical constructs of marketing research fit, technical fit and R&D objective fulfillment. Respondents were asked to what extent these statements described the R&D projects they were reporting. Participants were instructed to indicate the degree of their agreement with the statements on the above mentioned 7-point scale.

The fourth part included statements regarding the theoretical constructs of product superiority and product meaningfulness. Respondents were asked to what extent these statements described the biotechnological material or process resulting from the R&D projects they were reporting. Again, participants were asked to indicate the degree of their agreement with the statements on the 7-point scale described above.

The fifth part asked participants to provide information on the R&D project they were reporting in order to categorize their answers. This included information regarding the R&D project’s biotechnological area of activity (e.g., health/medicine, agricultural biotechnology, or industrial biotechnology), number of R&D project partners, size of the R&D project (i.e., average number of project members), R&D project budget, R&D project duration, respondents’ business units at the time of the reported R&D projects, respondents’ position at the time of the reported R&D projects, and type of biotechnological product. In addition, respondents were asked to give an assessment of how knowledgeable they felt in answering the question of the survey by means of Likert-type 7-point scale (1 = “not knowledgeable at all, 7 = “totally knowledgeable”).

In the sixth and final part, the respondents were asked whether they wished to receive a practice-oriented evaluation of the study results or not. In this regard, participants had the choice of providing their name and email address and were

assured that no information will be published that allows conclusions to be drawn about individual persons, institutions and/or companies. Finally, respondents were thanked for participating in the study.

Figure 16 visualizes the structure of the questionnaire.

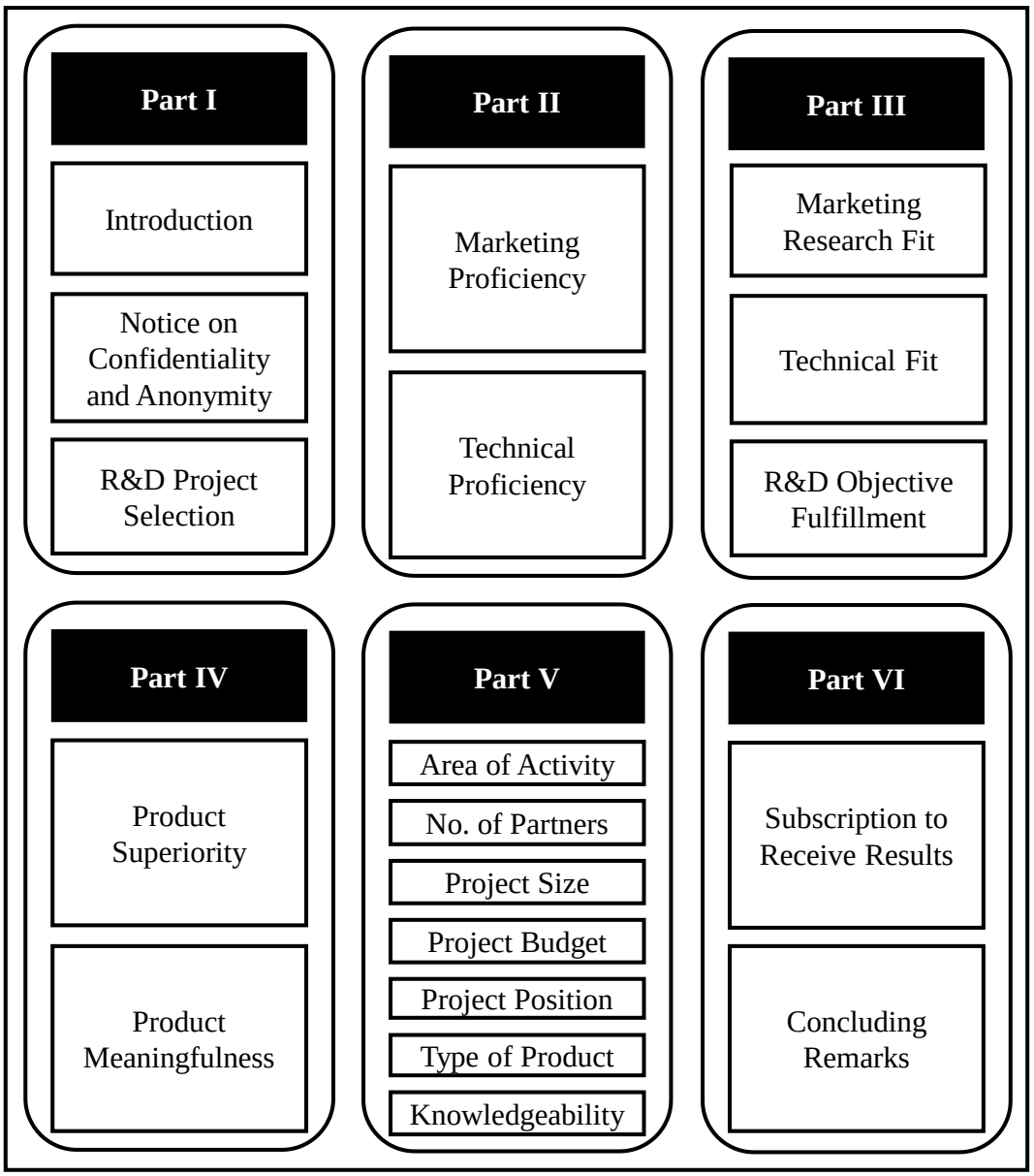

Figure 16: Structure of the questionnaire

4.5 Description of the Sample

A total of 15,134 potential respondents were contacted through personalized emails and invited to take part in the survey. Of these, 1,941 persons responded, which corresponds to a response rate of 12.83% (see Table 28). Feedback

received from contacted persons who did not participate in the survey showed that a major reason for the difference between the total sample and the number of individuals who responded is that not all persons who were invited to participate in the survey had prior experience with cooperative R&D projects between biotechnology firms and PRI. The experience of a potential informant with cooperative R&D projects between biotechnology firms and PRI could not be examined in advance, as no corresponding databases exist.

It has to be noted that some of the respondents only viewed the first pages of the questionnaire (e.g., for reasons of curiosity) but did not complete the survey. As a consequence, 1,337 questionnaires which had not been fully completed were removed from the sample.[32] Moreover, the data were adjusted with regard to respondents' self-assessment of knowledgeability (Kumar et al. 1993; Li/Calantone 1998). Respondents were asked how knowledgeable they are of a cooperative R&D project between at least one biotechnology firm and one PRI. Evidence of knowledgeability was assessed on a 7-point Likert scale (anchored at "not very knowledgeable"/"very knowledgeable") (Li/Calantone 1998, p. 20). Only cases with a self-assessment of knowledgeability value of 4 or higher were included in the empirical analysis. Thus, a total of 517 questionnaires were included in the empirical analysis, which corresponds to a net response rate of 3.42%.

Table 28: Field report

Field Report	Absolute Numbers	Percent
Total sample	15,134	100.00
Responses	1,941	12.83
Final sample	517	3.42

[32] This does not refer to missing values concerning control variables.

Table 29 depicts the distribution by respondents' type of organization at the time of the reported R&D projects. With a share of 52.42%, about half of all participants were members of a university at the time of the reported cooperative R&D project, followed by members of non-university research organizations (30.75%) and biotechnology firms (15.86%). Less than 1% of the respondents were affiliated with other types of organizations (e.g. management consultancies) at the time of the reported cooperative R&D project. This distribution is in line with the large number of PRI compared to the approximately 600 biotechnology firms in Germany (BIOCOM AG 2017).

Table 29: Distribution by respondents' type of organization at the time of the reported R&D projects

Respondents' Type of Organisation	Frequency	Percent
Biotechnology firm	82	15.86
University (incl. university hospital)	271	52.42
Non-university research institution	159	30.75
Other type of organization	5	0.97
Total	517	100

Table 30 shows the distribution by biotechnological area of activity of the reported R&D projects. In accordance to the dominating number of biotechnology firms active in the development of therapeutics and/or diagnostics for the field of human medicine, drug delivery, human tissue replacement (BIOCOM AG 2015, p. 10), more than half of the reported cooperative R&D projects between biotechnology firms and PRI involved R&D activities in the area of health/medicine. 19.15% of the reported cooperative R&D projects were located in the area of industrial biotechnology (i.e., development of biotechnological materials and processes for the handling of waste or sewage, for chemical

synthesis, for the extraction of raw materials and energy etc.; BIOCOM AG 2017, p. 13), 10.06% in the area of agricultural biotechnology (i.e., development of "[g]enetically modified plants, animals or microorganisms, as well as nongenetically modified plants grown using biotechnological procedures, for use in agriculture or forestry; BIOCOM AG 2017, p. 13), and 5.61% in the area non-specific applications (i.e., development of "[e]quipment or reagents based on biotechnological principles, for research or provision of services in this field ('ancillary industry')"). 4.84% of the reported cooperative R&D projects involved activities that were not assignable to a specific biotechnological area and only 3.29% of the reported cooperative R&D projects were located in the area of animal health.

Table 30: Distribution by biotechnological area of activity

Biotechnological Area of Activity	Frequency	Percent
Health/medicine	295	57.06
Animal health	17	3.29
Agricultural biotechnology	52	10.06
Industrial biotechnology	99	19.15
Non-specific applications	29	5.61
Not (yet) assignable	25	4.84
Total	517	~100

Table 31 illustrates the distribution by number of R&D project partners of the reported R&D project. Each reported cooperative R&D project consisted of at least of one biotechnology firm and one PRI. The majority of reported cooperative R&D projects included two partners (40.43%), followed by three project partners (27.85%), and five or more project partners (20.12%). 11.41% of the reported

R&D projects involved four project partners. One respondent did not specify the number of R&D project partners.

Table 31: Distribution by number of R&D project partners

Number of R&D Project Partners	Frequency	Percent
2	209	40.43
3	144	27.85
4	59	11.41
5 or more	104	20.12
Not specified	1	0.19
Total	517	100

Table 32 provides information on the distribution by size of the reported R&D projects. Most of the reported cooperative R&D projects consisted of 5 to 10 project team members (47.20%), followed by projects with less than 5 members (33.27%), and projects with 11 to 15 project team members (10.64%). Cooperative R&D projects with more than 20 project team members (4.84%) and 16 to 20 (4.06%) project team members were the least common group of reported projects.

Table 32: Distribution by size of R&D projects (average number of project team members)

Average Number of Project Team Members	Frequency	Percent
< 5	172	33.27
5-10	244	47.20
11-15	55	10.64
16-20	21	4.06
> 20	25	4.84
Total	517	~100

Table 33 depicts the distribution by R&D project budgets. With a share of 37.52%, most cooperative R&D projects between biotechnology firms and PRI had a budget of 100,000 – 499,999 euros, followed by projects with a budget of 1,000,000 – 10,000,000 euros (19.92%), of 500,000 – 999,999 euros (17.79%), of less than 100,000 euros (16.05%), as well as more than 10,000,000 euros (2.71%). 6% of the respondents did not specify the budget of the reported cooperative R&D projects.

Table 33: Distribution by R&D project budgets

R&D Project Budget (in euros)	Frequency	Percent
< 100,000	83	16.05
100,000 – 499,999	194	37.52
500,000 – 999,999	92	17.79
1,000,000 – 10,000,000	103	19.92
> 10,000,000	14	2.71
Not specified	31	6.00
Total	517	~100

Table 34 presents the distribution by duration of the reported R&D projects. The majority of the reported R&D projects lasted between 25 to 36 months (40.81%), followed by projects with a duration of 12 to 24 months (28.82%), of 37 to 48 months (11.80%), and of less than 12 months (7.93%). Projects with a duration of 49 to 60 months (5.80%) or even more than 60 months (4.84%) do not appear very frequently in the sample examined.

Table 34: Distribution by duration of R&D projects

R&D Project Duration (in months)	Frequency	Percent
< 12	41	7.93
12-24	149	28.82
25-36	211	40.81
37-48	61	11.80
49-60	30	5.80
> 60	25	4.84
Total	517	100

Table 35 shows the distribution with regard to the business units the respondents were affiliated with at the time of the reported R&D projects. Since the unit of analysis is the cooperative R&D project between biotechnology firms and PRI, the vast majority of the respondents were members of the R&D department (73.11%), followed by members of the management department (8.70%), and professionals active in the medical field (8.51%; i.e., members of university hospitals). Only a few respondents were members of the production department (0.97%), marketing and sales department (0.58%), as well as professionals of the controlling (0.39%) and accounting business unit (0.19%) at the time of the reported cooperative R&D project. Approximately 7% of the respondents belonged to business units not mentioned in the questionnaire, and two respondents did not specify the business units they were working at the time of the reported R&D projects.

Table 35: Distribution by respondents' business unit at the time of the reported R&D projects

Respondents' Business Unit	Frequency	Percent
R&D	378	73.11
Production	5	0.97
Purchase	0	0.00
Marketing and sales	3	0.58
Controlling	2	0.39
Accounting	1	0.19
Management	45	8.70
Health/medical field	44	8.51
Other business unit	37	7.16
Not specified	2	0.39
Total	517	100

Table 36 depicts the distribution by respondents' position at the time of the reported R&D projects. Most of the respondents were directly responsible for the reported cooperative R&D project by holding the position of project manager (43.91%), followed by respondents who were project members (37.14%), and professionals in the general R&D management (10.64%). A minority of the respondents reported that they were not directly involved in the reported R&D project (4.26%) or were holding a position not mentioned in the questionnaire (4.06%) such as medical doctors or consultants.

Table 36: Distribution by respondents' position at the time of the reported R&D projects

Respondents' Position	Frequency	Percent
Project Member	192	37.14
Project Manager	227	43.91
General R&D Management	55	10.64
Not directly involved	22	4.26
Other position	21	4.06
Total	517	~100

Table 37 illustrated the distribution by type of the biotechnological product that was developed in the reported R&D projects. Most of the projects involved both the development of a biotechnological material and process (37.91%), followed by projects that solely focused on the development of a biotechnological process (35.01%) or biotechnological material (27.08%).

Table 37: Distribution by type of biotechnological product

Type of Biotechnological Product	Frequency	Percent
Biotechnological material	140	27.08
Biotechnological process	181	35.01
Both	196	37.91
Total	517	100

4.6 Descriptive Analysis

Tables 38 to 41 illustrate the descriptive statistics concerning the variables of the model. In particular, the model's constructs are considered with regard to the mean (i.e., the mean latent variable scores) and the standard deviation (i.e., the mean absolute deviation). Each item was measured on a Likert-type 7-point scale. Respondents were asked to indicate the degree of their agreement by selecting a number between 1 ("don't agree at all") and 7 ("totally agree") under each statement on the scale, where the numbers between 1 and 7 corresponded to the different degrees of agreement.

Most of the variables (i.e., technical fit, R&D objective fulfillment, and product competitive advantage) mean values are in the range of 5 points, indicating a high level of agreement with the respective statements, followed by marketing proficiency and technical proficiency with values in the range of 4 points, as well as marketing research fit, which has a mean value of approximately 3.6. For all constructs, standard deviations range between 1 and 2, with technical fit having the lowest (1.068) and marketing proficiency (1.966) having the highest standard deviation.[33]

[33] "Small standard deviations (relative to the value of the mean itself) indicate that the data points are close to the mean. A large standard deviation (relative to the mean) indicates that the data points are distant from the mean (i.e., the mean is not an accurate representation of the data). A standard deviation of 0 would mean that all of the scores were the same" (Field et al. 2012, p. 39).

Table 38: Descriptive statistics (I)

Variable	Indicator	Item Formulation	Mean	Standard Deviation
Technical fit	TF_1	The scientific expertise available in the project was more than adequate for this R&D project.	5.273	1.068
	TF_2	The resources available in the project for R&D (e.g., technical equipment) were more than adequate for this R&D project.		
	TF_3	The know-how available in the project for industrial production was more than adequate for this R&D project.		
	TF_4	The resources available in the project for industrial production were more than adequate for this R&D project.		
Marketing research fit	MRF_1	The know-how available in the project for conducting marketing research (e.g., for analyzing market potential) was more than adequate for this R&D project.	3.653	1.645
	MRF_2	The resources available in the project for conducting marketing research (e.g., financial resources) were more than adequate for this R&D project.		

Table 39: Descriptive statistics (II)

Variable	Indicator	Item Formulation	Mean	Standard Deviation
Marketing proficiency	MP_1	An initial evaluation of the R&D project based on criteria relevant to success (e.g., feasibility, project scope, exploitation potential) has been done more than adequately.	4.723	1.966
	MP_2	A determination of desirable features of the biotechnological material or process under development has been done more than adequately.		
	MP_3	An identification of potential markets and their trends for the biotechnological material or process has been done more than adequately.		
	MP_4	Conducting a market study: A detailed analysis of market potential, preferences of potential users, etc. has been done more than adequately.		
	MP_5	An appraisal of existing and potential competitors and their biotechnological inventions (materials or processes) has been done more than adequately.		
	MP_6	An identification of characteristics that would differentiate the biotechnological material or process and contribute to its sale has been done more than adequately.		

Table 40: Descriptive statistics (III)

Variable	Indicator	Item Formulation	Mean	Standard Deviation
Technical proficiency	TP_1	An evaluation of the feasibility of developing and manufacturing a biotechnological material or process with the desired features has been done more than adequately.	4.782	1.210
	TP_2	The development of the biotechnological material or process according to the desired features has been done more than adequately.		
	TP_3	An evaluation of laboratory tests to determine the actual features of the biotechnological material or process has been done more than adequately.		
	TP_4	Tests on prototypes of the biotechnological material or process have been carried out more than adequately.		
	TP_5	An elaboration of a detailed plan for the industrial production of the material or for the industrial application of the process has been done more than adequately.		
	TP_6	The consideration of the costs and quality of the biotechnological material or process has been done more than adequately throughout the entire R&D project.		
R&D objective fulfillment	OF_1	We are satisfied with the project results.	5.157	1.419
	OF_2	The project results have fulfilled the initial expectations.		
	OF_3	The project has provided satisfactory results for all project partners involved.		

Table 41: Descriptive statistics (IV)

Variable	Indicator	Item Formulation	Mean	Standard Deviation
Product competitive advantage (higher-order construct)	LV_PM	The biotechnological material or process is of great benefit to the user.	5.534	1.128
		The biotechnological material or process is of great value to the user.		
		The biotechnological material or process has many advantages.		
	LV_PS	The developed material or process has unique features or performance characteristics that are not available from biotechnological inventions of the competition.		
		The developed material or process is superior to competing biotechnological inventions in terms of meeting the needs of users.		
		The quality of the developed material or process is - however quality is defined by the user - superior to competing biotechnological inventions.		

4.7 Structural Equation Modelling

Structural equation modeling (SEM) is used to test the hypothesized relationships between latent variables (McDonald/Ho 2002, p. 64; Hoe 2008, p. 76; Hair et al. 2016, p. 328). Latent variables are the theoretical or conceptual elements in the structural model (i.e., technical fit, marketing research fit, technical proficiency, marketing proficiency, R&D objective fulfillment, and product competitive advantage in the present study) (Hair et al. 2016, p. 320). The special feature of SEM is its ability to evaluate the measurement of latent variables and at the same time to test the relationships between latent variables (Hair et al. 2014, p.106).

There are two types of SEM: one is covariance-based SEM (CB-SEM), and the other is variance-based SEM (i.e., PLS-SEM). CB-SEM and PLS-SEM have been developed to pursue different objectives (Barroso et al. 2010, p. 429; see Figure 17):

- CB-SEM is used to confirm (or reject) theories by examining how well a structural model can estimate the covariance matrix of a data set (Hair et al. 2016, p. 315). The algorithm seeks to estimate the model's parameters (i.e., loads and path values) in an attempt to minimize the difference between the sample covariance and those expected by the conceptual model. Thus, the algorithm tries to reproduce the covariance matrix of the observed measures to see how well the conceptual model fits the data. CB-SEM focuses on overall model fit, which means this approach is aimed at testing a strong theory. CB-SEM is therefore particularly suitable for confirmatory research (Barroso et al. 2010, p. 429f.).
- PLS-SEM is a statistical analysis technique to estimate structural equation models by maximizing the explained variance of the endogenous latent variables[34] (Hair et al. 2016, p. 324). Since PLS-SEM focuses on the explanation of variances, it has a prediction-oriented character (i.e., the objective is to predict output values through input values; Sarstedt et al. 2014, p. 155). Focusing primarily on prediction[35], PLS-SEM is "particularly useful for studies on the sources of competitive advantage and success driver studies" (Hair et al. 2016, p. 86). The concept of PLS-SEM is applied in the current analysis.

[34] "A latent variable that only explains other latent variables (only outgoing relationships in the structural model) is called exogenous, while latent variables with at least one incoming relationship in the structural model are called endogenous" (Hair et al. 2016, p. 320).

[35] Prediction is an essential part of theory assessment (Colquitt/Zapata-Phelan's 2007, p. 1281; Bagozzi/Yi 2012, p. 23), a characteristic of a strong theory (Bagozzi/Yi 2012, p. 23), as well as the foundation to provide guidelines for decision-making (Sarsted et al. 2014, p. 155).

Criterion	CB-SEM	PLS-SEM
Objective	Best possible reproduction of the empirical variance-covariance matrix	Best possible prediction of the data matrix with regard to the target variables
Focus	Theory testing	Prediction
Methodology	Factor analytical approach with simultaneous estimation of all parameters of the causal model	Regression-analytical approach for two-step estimation of measurement models and structural model
Data base	Variance-covariance matrix	Data matrix
Structural model	Recursive and non-recursive models	Only recursive models
Measument models	Primarily reflective	Reflective and formative
Distributional assumptions	Normal distribution	None
Quality assessment	Global and local inferential statistical quality measures	Partial quality criteria regarding the prediction of the data matrix

Figure 17: Fundamental differences between CB-SEM and PLS-SEM[36]

PLS-SEM was developed by Herman O.A. Wold (1974, 1980, 1982) as a predictive and robust statistical analysis technique (Dijkstra 2010, p. 24). Since then, PLS-SEM has been used in a broad number of disciplines including marketing (Hair, Sarstedt, Ringle, & Mena 2012), strategic management (Hair, Sarstedt, Pieper, & Ringle 2012), management information systems (Ringle et al. 2012), operations management (Peng/Lai 2012), and accounting (Lee et al. 2011).

The core of the statistical analysis technique is the PLS-SEM algorithm, which estimates the scores of all latent variables based on the proposed path model[37] and the available empirical data (i.e., the indicator data[38]). The scores of

[36] Figure adapted from Weiber/Mühlhaus (2014, p. 74).

[37] Path models "are diagrams that visually display the hypotheses and variable relationships that are examined when structural equation modeling is applied" (Hair et al. 2016, p. 324).

the latent variables then serve to estimate the relationships in the path model (Hair et al. 2016, p. 325). In the beginning, the relationships between the latent variables (i.e., the path coefficients[39]) are not yet known. To estimate the path coefficients, the algorithm will calculate a score for each latent variable on the basis of its respective indicator data. After the algorithm has calculated the scores of the latent variables, these scores are used as input to conduct partial regression calculations. A partial regression model is calculated for each endogenous latent variable. The result of these calculations is the estimation of all relationships in the measurement model (i.e., outer loadings[40] and weights[41]) and all relationships in the structural model (i.e., the path coefficients). All partial regression models are estimated by an iterative algorithmic procedure, which ends when the change in the outer weights between two consecutive iterations is smaller than a predefined stop criterion (Hair et al. 2016, p. 83ff.). If the research objective is concerned with prediction and involves explaining the variance of important target constructs (e.g., competitive advantages) by different explanatory constructs (e.g., different sources of competitive advantages), PLS-SEM will be the appropriate statistical analysis technique (Reinartz et al. 2009, p. 340; Hair, Sarstedt, Pieper, & Ringle 2012, p. 321).

Another important consideration when selecting the appropriate SEM technique is the type of measurement specification of the latent variables. A

[38] Indicators are "directly measured observations (raw data), generally referred to as either items or manifest variables, represented in path models as rectangles. They are also available data (e.g., responses to survey questions or collected from company databases) used in measurement models to measure the latent variables; in SEM, indicators are often called manifest variables" (Hair et al. 2016, p. 319)

[39] Path coefficiencts "are estimated path relationships in the structural model (i.e., between the constructs in the model). They correspond to standardized betas in a regression analysis" (Hair et al. 2016, p. 324).

[40] Outer loadings "are the estimated relationships in reflective measurement models (i.e., arrows from the latent variable to its indicators). They determine an item's absolute contribution to its assigned construct. Loadings are of primary interest in the evaluation of reflective measurement models but are also interpreted when formative measures are involved" (Hair et al. 2016, p. 323).

[41] Outer weights "are the results of a multiple regression of a construct on its set of indicators. Weights are the primary criterion to assess each indicator's relative importance in formative measurement models" (Hair et al. 2016, p. 323).

distinction is made between two different types of measurement specifications: reflective and formative measurement models. Reflective measurement models are based on the idea that the indicators represent the effects (or manifestations) of an underlying latent variable. The direction of causality is from the latent variable to the indicators. The reflective indicators function as a representative sample of all the possible indicators available within the domain of the latent variable. Thus, the reflective indicators should be highly correlated and dropping an indicator should not change the conceptual domain of the latent variable (Jarvis et al. 2003, p. 203; see Figure 18). In the current analysis, technical fit, marketing research fit, and R&D objective fulfillment are reflectively measured constructs.

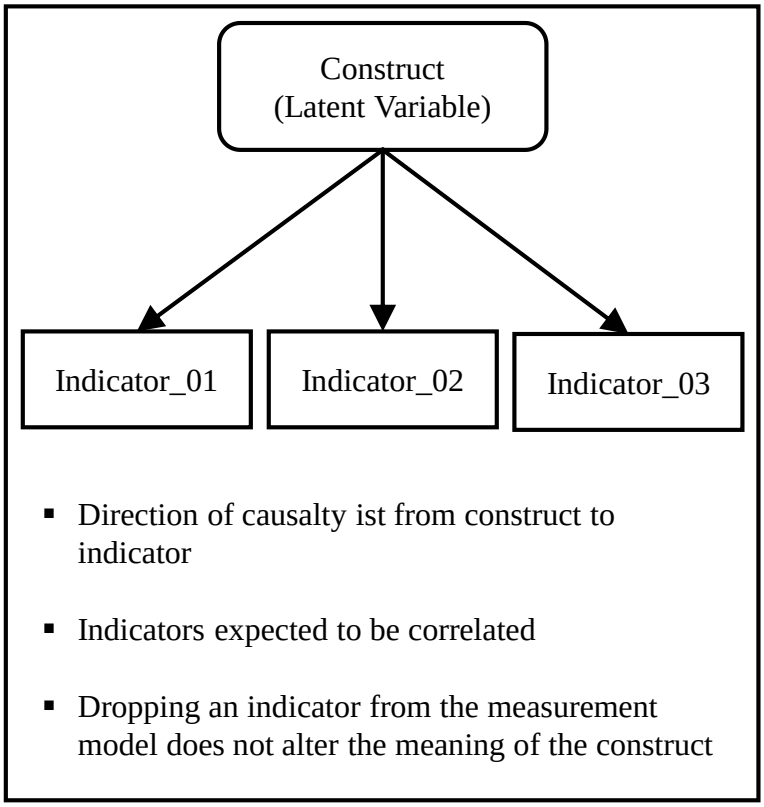

Figure 18: Reflective measurement models[42]

Formative measurement models are based on the idea that the indicators are defining characteristics of the latent variable (Jarvis et al. 2003, p. 203). The direction of causality is from the indicators to the latent variable. The indicators "form the construct by means of linear combinations" (Hair et al. 2016, p. 47). Each formative indicator captures a certain aspect of the latent variable's domain.

[42] Figure adapted from Jarvis et al. (2003, p. 201).

Taken together, the indicators determine the meaning of the latent variable (Hair et al. 2016, p. 47). Thus, the formative indicators do not need to be correlated, but dropping an indicator might change the conceptual domain of the latent variable (Jarvis et al. 2003, p. 203; see Figure 19). Formative constructs are particularly useful when multidimensional constructs (e. g. the sources of competitive advantages) are to be investigated (Hair, Sarstedt, Pieper, & Ringle 2012, p. 321; Hair et al. 2014, p. 117). In the current analysis, technical proficiency, marketing proficiency, and product competitive advantage are formatively measured constructs.

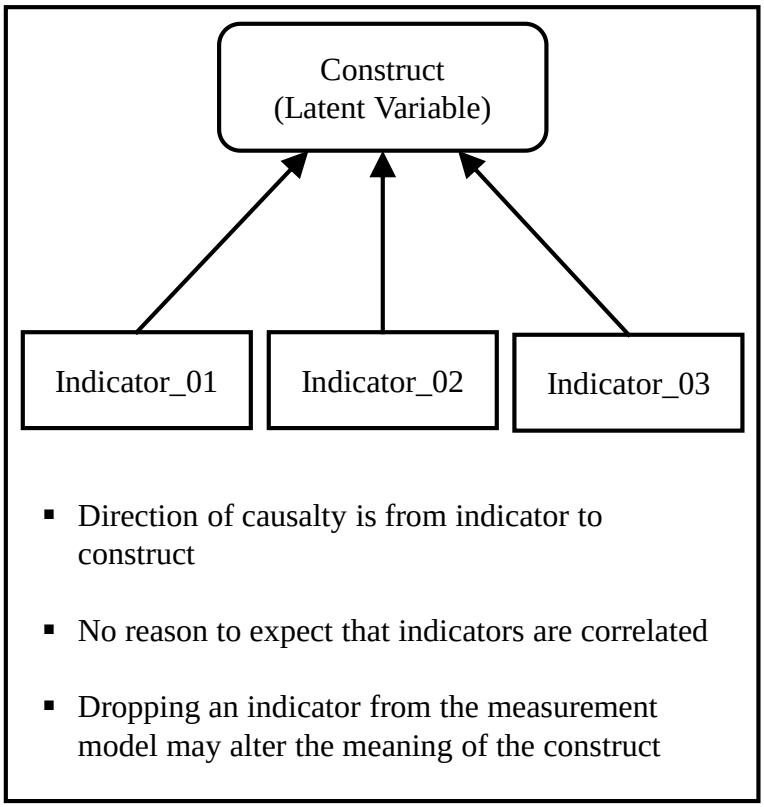

Figure 19: Formative measurement models[43]

One of the central advantages of PLS-SEM is the easy integration of formative measurement models. Although CB-SEM is in principle able to deal with formative measurement models, their inclusion can be problematic and entails extensive limitations on the model (MacCallum/Browne 1993). Instead, PLS-SEM is the recommended technique that should be used for models with formative measurement models (Chin 1998a, p. ixf.).

[43] Figure adapted from Jarvis et al. (2003, p. 201).

4.8 Evaluation of PLS-SEM Results

Evaluating the PLS-SEM results entails an extensive evaluation procedure (Götz et al. 2010, p. 693ff.), which can be described as a two-step process (Hair et al. 2016, p. 106; see Figure 20). The first step involves the evaluation of the (reflective and formative) measurement models[44]. The rationale of this initial quality assessment is the essential prerequisite that the measures adequately represent the constructs of interests before using them to investigate the structural relationships (i.e., the relationships between the constructs) (Hair et al. 2011, p. 144). The second step includes the actual evaluation of the structural model estimates (i.e., hypotheses testing).[45]

[44] Latent variables are either specified as reflective or formative measurement models, which need to fulfill different quality criteria. A measurement model "is an element of a path model that contains the indicators and their relationships with the constructs" (Hair et al. 2016, p. 321). Please note that the terms "latent variable" and "construct" are used interchangeable.

[45] The research model was estimated using SmartPLS 3 (Ringle et al. 2015).

Evaluation of the Measurement Models	
Reflective Measurement Models	**Formative Measurement Models**
Internal Consistency Reliability • *Cronbach's Alpha* • *Composite Reliability* Convergent Validity • *Indicator Reliability* • *Average Variance Extracted* Discriminant Validity • *Cross-loadings* • *Fornell-Larcker Criterion* • *Heterotrait-monotrait Ratio*	Collinearity Assessment Indicators' Relative Contribution to the Constructs: Indicator Weights & Significance of Weights
Evaluation of the Structural Model	
Collinearity Assessment Structural Model Path Coefficient Coefficient of Determination (R^2 Value) Effect Size f^2 Prediction Relevance Q^2 and Effect Size q^2	

Figure 20: Evaluation of PLS-SEM results[46]

4.8.1 Evaluation of the Measurement Models

4.8.1.1 Reflective Measurement Models

A reflective measurement model "is a type of measurement model setup in which measures represent the effects (or manifestations) of an underlying construct. Causality is from the construct to its measures (indicators)" (Hair et al. 2016, p. 326). The current analysis includes three latent variables that are specified as reflective measurement models: technical fit, marketing research fit, and R&D objective fulfillment. The evaluation of reflective measurement models comprises the evaluation of internal consistency reliability, convergent validity, and discriminant validity (Hair et al. 2016, p. 104ff.; see Figure 21).

[46] Figure adapted from Hair et al. (2016, p. 106).

Evaluation of Reflective Measurement Models

Internal Consistency Reliability
- *Cronbach's Alpha*
- *Composite Reliability*

Convergent Validity
- *Indicator Reliability*
- *Average Variance Extracted*

Discriminant Validity
- *Cross-loadings*
- *Fornell-Larcker Criterion*
- *Heterotrait-monotrait Ratio*

Figure 21: Evaluation of reflective measurement models[47]

4.8.1.1.1 Internal Consistency Reliability

Internal consistency reliability "is a form of reliability used to judge the consistency of results across items on the same test. It determines whether the items measuring a construct are similar in their scores (i.e., if the correlations between the items are large)" (Hair et al. 2016, p. 320). To evaluate internal consistency reliability, Cronbach's alpha and composite reliability are examined.

The most common measure of internal consistency reliability is Cronbach's alpha (Götz et al. 2010, p. 695; Hair, Sarstedt, Ringle, & Mena 2012, p. 424). Cronbach's alpha evaluates how well a set of indicators measures a latent variable (Götz et al. 2012, p. 695). Cronbach's alpha values vary between 0 and 1, with higher values indicating higher levels of reliability. A common threshold for sufficient values of Cronbach's alpha is 0.70 (Nunnally 1978, p. 245). The resulting Cronbach's alpha values are presented in Table 42. The specific Cronbach's alpha values (0.724 for technical fit, 0.830 for marketing research fit, and 0.934 for R&D objective fulfillment) are all above the 0.70 threshold value. Thus, the analysis of Cronbach's Alpha suggests that internal consistency reliability has been established.

[47] Figure adapted from Hair et al. (2016, p. 106).

Table 42: Cronbach's alpha

Construct	Cronbach's Alpha
Technical fit	0.724
Marketing research fit	0.830
R&D objective fulfillment	0.934

Composite reliability is a common alternative to Cronbach's alpha as a measure of internal consistency reliability (Hair et al. 2016, p. 112). In contrast to Cronbach's alpha, composite reliability calculations use the actual factor loadings instead of equal weighting (Götz et al. 2010, p. 695). Composite reliability values vary between 0 and 1, with higher values indicating higher levels of reliability. A common threshold for sufficient values of composite reliability is 0.7 (Bagozzi/Yi 1988, p. 82; Hair et al. 2012b, p. 429). The resulting composite reliability values are presented in Table 43. All composite reliability values exceed the threshold value of 0.70. With values of 0.826 (technical fit), 0.920 (marketing research fit), and 0.958 (R&D objective fulfillment), all three reflective constructs have high levels of internal consistency reliability. Thus, the analysis of composite reliability suggests that internal consistency reliability has been established.

Table 43: Composite reliability

Construct	Composite Reliability
Technical fit	0.826
Marketing research fit	0.920
R&D objective fulfillment	0.958

4.8.1.1.2 Convergent Validity

Convergent validity is defined as the extent to which a measure (i.e., an indicator) correlates highly with other methods designed to measure the same construct (i.e., latent variable) (Churchill 1979, p. 70). In the rationale of reflective measurement models, indicators of a latent variable are understood as alternative measures of the same construct (Jarvis et al. 2003, p. 203; Hair et al. 2016, p. 112f.). Thus, the indicators of a latent variable should be positively correlated, since all indicators are supposed to be interchangeable measures of the same reflective construct (Jarvis et al. 2003, p. 203). To evaluate convergent validity, indicator reliability and average variance extracted are examined.

Indicator reliability is a measure to assess which part of an indicator's variance can be explained by its latent variable (Götz et al. 2010, p. 694). An indicator's variance can be explained by its latent variable and variance of measurement error. Sufficient indicator reliability means that at least 50% of an indicator's variance is explained by its latent variable (Hair et al. 2016, p. 113f.). Since indicator reliability is the square of a standardized indicator's outer loading (Hair et al. 2016, p. 319), the common threshold value of an indicator's loading should be above 0.7 (Hulland 1999, p. 198). The resulting indicator reliability values are presented in Table 44. All outer loadings of the reflective constructs of marketing research fit and R&D objective fulfillment are well above the threshold value of 0.70. Regarding the reflective construct of technical fit, the indicators TF_1 (outer loading: 0.646) and TF_2 (outer loading: 0.642) are below the threshold. However, it is not uncommon to retain indicators with outer loadings between 0.4 and 0.7 (Hulland 1999, p. 198f.) on the basis of their contribution to content validity[48] (Hair et al. 2016, p. 113f.). According to Hair (2016, p. 113f.), indicators with outer loadings between 0.4 and 0.7 should only be removed if the indicator's elimination increased composite reliability above the suggested threshold. Since the composite reliability value of technical fit is well above the threshold and internal consistency reliability has already been established (see Section 4.8.1.1.1), the indicators TF_1 and TF_2 are retained. In sum, the analysis of indicator reliability suggests that convergent validity has been established.

[48] Content validity "is a subjective but systematic evaluation of how well the domain content of a construct is captured by its indicators" (Hair et al. 2016, p. 315).

Table 44: Indicator reliability

Indicator	Indicator Reliability
TF_1	0.646
TF_2	0.642
TF_3	0.869
TF_4	0.792
MRF_1	0.946
MRF_2	0.899
OF_1	0.945
OF_2	0.951
OF_3	0.924

Average variance extracted (AVE) is a measure to assess the degree to which a latent variable explains the variance of its indicators (Hair et al. 2016, p. 312). The AVE measure is conceptualized "as the grand mean value of the squared loadings of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators)" (Hair et al. 2016, p. 115). A common threshold for sufficient values of AVE is 0.5 (Bagozzi/Yi 1988, p. 82). An AVE value of less than 0.5 indicates that the variance due to measurement error is larger than the variance captured by the construct (Fornell/Larcker 1981, p. 46). The resulting AVE values are presented in Table 45. The AVE values of technical fit (0.547), marketing research fit (0.852), and R&D objective fulfillment (0.884) are well above the required minimum level of 0.50. Thus, the analysis of AVE suggests that convergent validity has been established.

Table 45: AVE

Construct	AVE
Technical fit	0.547
Marketing research fit	0.852
R&D objective fulfillment	0.884

4.8.1.1.3 Discriminant Validity

Discriminant validity is a methodological complement to convergent validity (Hulland 1999, p. 199). Discriminant validity "is the extent to which a construct is truly distinct from other constructs, in terms of how much it correlates with other constructs, as well as how much indicators represent only a single construct" (Hair et al. 2016, p. 316). When discriminant validity is not established, latent variables might have an effect on the variation of more than just the variables to which they are related to in a theoretical model (Farrell 2010, p. 325). In such a situation, "researchers can not be certain whether results confirming hypothesized structural paths are real or whether they are a result of statistical discrepancies" (Farrelll 2010, p. 324). To evaluate discriminant validity, indicators' cross-loadings, the Fornell–Larcker criterion, and the heterotrait-monotrait ratio are examined.

Cross-loadings represent an indicator's correlation with other latent variables in the model (Hair et al. 2016, p. 315). To establish discriminant validity, an indicator's outer loading (i.e., its correlation) on its intended latent variable should be higher than any of its cross-loadings (i.e., its correlation) on other latent variables in the model (Hair et al. 2016, p. 115). Table 46 shows the loadings and cross-loadings for every indicator. For example, indicator TF_1 has the highest value for the loading with its corresponding construct of technical fit (0.646), while all cross-loadings with other constructs are considerably lower (e.g., TF_1 on marketing research fit: 0.197). The same finding holds for the other

indicators of technical fit as well as the indicators measuring marketing research fit and R&D objective fulfillment. Thus, the analysis of cross-loadings suggests that discriminant validity has been established.

Table 46: Cross-loadings

	Technical fit	Marketing research fit	Technical proficiency	Marketing proficiency	R&D objective fulfillment	Product competitive advantage
TF_1	*0.646*	0.197	0.368	0.320	0.343	0.349
TF_2	*0.642*	0.135	0.247	0.241	0.152	0.122
TF_3	*0.869*	0.418	0.532	0.458	0.266	0.260
TF_4	*0.792*	0.413	0.433	0.372	0.186	0.106
MRF_1	0.389	*0.946*	0.477	0.521	0.211	0.257
MRF_2	0.386	*0.899*	0.377	0.414	0.092	0.117
OF_1	0.301	0.121	0.450	0.360	*0.945*	0.436
OF_2	0.303	0.187	0.459	0.385	*0.951*	0.476
OF_3	0.326	0.179	0.430	0.361	*0.924*	0.431

To satisfy the requirements of discriminant validity, the Fornell-Larcker criterion (Fornell/Larcker 1981, p. 46) demands that the square root of the AVE of each latent variable is higher than the latent variable's highest correlation with any other construct in the structural model (Hair et al. 2016, p. 129). The rationale of the Fornell-Larcker criterion is that a latent variable shares more variance with its own indicators than with any other latent variable (Hair et al. 2016, p. 116).

Table 47 presents the results of the Fornell-Larcker criterion evaluation with the square root of the reflective constructs' AVE on the diagonal and the

correlations between the constructs in the off-diagonal position. For example, the reflective construct of technical fit has a value of 0.740 for the square root of its AVE, which needs to be compared with all correlation values in the column of 1.[49] Overall, the square roots of the AVEs for the reflective constructs of technical fit (0.740), marketing research fit (0.923), and R&D objective fulfillment (0.940) are all higher than the correlations of these constructs with other latent variables in the model, thus indicating all constructs are valid measures of unique concepts (Hair et al. 2016, p. 128f.). To conclude, the analysis of the Fornell-Larcker criterion suggests that discriminant validity has been established.

[49] Note that for other reflective specified latent variables, you need to consider the correlations in both row and column.

Table 47: Fornell-Larcker Criterion

	1	2	3	4	5	6	7	8	9
1 Technical fit	*0.740*								
2 Marketing research fit	0.419	*0.923*							
3 Technical proficiency	0.558	0.470							
4 Marketing proficiency	0.481	0.513	0.712						
5 R&D objective fulfillment	0.329	0.173	0.475	0.392	*0.940*				
6 Product competitive advantage	0.295	0.213	0.467	0.479	0.477				
7 Number project partners	-0.065	-0.060	-0.060	-0.028	-0.076	-0.074	1.000		
8 Project duration	0.000	0.050	0.052	0.028	-0.038	0.062	0.333	1.000	
9 Size project team	0.050	0.063	0.063	0.114	-0.014	0.001	0.001	0.415	1.000

Note: Table shows the results of the Fornell-Larcker criterion assessment with the square root of the reflective constructs' AVE on the diagonal (in italics) and the correlations between the constructs in the off-diagonal position.

Though the examination of cross-loadings and the Fornell-Larcker criterion are the dominant means for assessing discriminant validity in extant research, prior research has shown that these evaluation approaches do not

reliably detect lack of discriminant validity in some research situations (Henseler et al. 2015, p. 115). As a consequence, it is recommended to additionally examine the heterotrait-monotrait ratio (HTMT) (Henseler et al. 2015, p. 115f.; Hair et al. 2016, p. 118). HTMT "is an estimate of what the true correlation between two constructs would be, if they were perfectly measured (i.e., if they were perfectly reliable). HTMT is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the heterotrait-heteromethod correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (i.e., the monotrait-heteromethod correlations)" (Hair et al. 2016, p. 318). According to Henseler et al. (2016, p. 121), a HTMT value of above 0.90 indicates a lack of discriminant validity. The resulting HTMT ratio values are presented in Table 48. As can be seen, the HTMT ratio values are all clearly under the threshold value of 0.90. In addition, all HTMT values are significantly different from 1.[50] Thus, the analysis of the HTMT ratio suggests that discriminant validity has been established.

[50] The level of significance was tested by using the bootstrapping procedure. Bootstrapping "is a resampling technique that draws a large number of subsamples from the original data (with replacement) and estimates models for each subsample. It is used to determine standard errors of coefficients to assess their statistical significance without relying on distributional assumptions." (Hair et al. 2016, p. 313). As recommended by Hair, Sarstedt, Ringle, & Mena (2012, p. 429) and Hair et al. (2016, p. 160), the following options were selected using the bootstrapping procedure in SmartPLS 3 (Ringle et al. 2015): the selected number of bootstrap samples was 5000 (subsamples); the no sign change option was chosen to obtain the most conservative results (sign change option); the number of bootstrap cases equalled the number of valid observations (i.e., 517 observations).

Table 48: HTMT ratio

	1	2	5	7	8	9
1 Technical fit						
2 Marketing research fit	0.510					
5 R&D objective fulfillment	0.390	0.186				
7 Number project partners	0.078	0.076	0.079			
8 Project duration	0.017	0.015	0.040	0.333		
9 Size project team	0.072	0.096	0.021	0.455	0.415	

4.8.1.1.4 Conclusion

The evaluation of the reflective measurement models included analyses of internal consistency reliability (i.e., analyzing Cronbach's alpha and composite reliability), convergent validity (i.e., analyzing indicator reliability and AVE), as well as discriminant validity (i.e., analyzing cross-loadings, Fornell-Larcker criterion, and HTMT). A summary of the results is presented in Table 49. The evaluation of the reflective measurement models suggests that the reflective measures are reliable and valid. To conclude, the assessment provides evidence that the measurement quality of the reflective measured latent variables (i.e., technical fit, marketing research fit, and R&D objective fulfillment) complies with the requirements of PLS-SEM.

Table 49: Reflective measurement models evaluation

Latent Variable	Indicator	Convergent Validity		Internal Consistency Reliability		Discriminant Validity		
		Indicator Reliability	AVE	Composite Reliability	Cronbach's Alpha	Cross-Loading	Fornell–Larcker Criterion	HTMT
		>0.70	>0.50	>0.70	>0.70	Outer loadings higher than all its cross-loadings?	Square root of each construct's AVE greater than its highest correlation with any other construct?	HTMT below 0.90?
Technical fit	TF_1	0.646	0.547	0.826	0.724	Yes	Yes	Yes
	TF_2	0.642						
	TF_3	0.869						
	TF_4	0.792						
Marketing research fit	MRF_1	0.946	0.852	0.920	0.830	Yes	Yes	Yes
	MRF_2	0.899						
R&D objective fulfillment	OF_1	0.945	0.884	0.958	0.934	Yes	Yes	Yes
	OF_2	0.951						
	OF_3	0.924						

4.8.1.2 Formative Measurement Models

A formative measurement model "is a type of measurement model setup in which the direction of the arrows is from the indicator variables to the construct, indicating the assumption that the indicator variables cause the measurement of the construct" (Hair et al. 2016, p. 317). The current analysis includes three latent variables that are specified as formative measurement models: technical proficiency, marketing proficiency, and product competitive advantage. The evaluation of formative measurement models comprises the assessment of collinearity of the indicators, as well as the assessment of indicator weights and the significance of weights (Hair et al. 2016, p. 137ff.; see Figure 22).

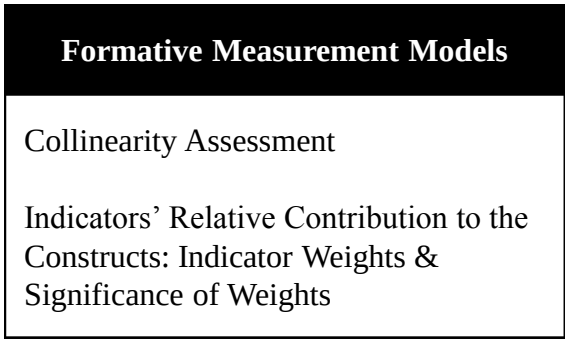

Figure 22: Evaluation of formative measurement models[51]

4.8.1.2.1 Collinearity Assessment

Collinearity of formative indicators arises when two indicator variables are highly correlated. However, and unlike reflective indicators, formative indicators cause or form[52] the measurement of the latent variable they are assigned to. Formative constructs (latent variables) are regarded as linear combinations of their indicators. Each formative indicator captures a certain aspect of the latent variable's domain. Taken together, the indicators determine the meaning of the latent variable (Hair et al. 2016, p. 47). Thus, formative indicators do not need to

[51] Figure adapted from Hair et al. (2016, p. 106).

[52] There is an ongoing discussing of whether formative indicators cause or form a latent variable. This subtle difference can be neglected in the current thesis, since all "variance-based SEM techniques model latent variables as composites; that is, they create proxies as linear combinations of indicator variables" (Henseler et al. 2016, p. 408). For more information on that topic, please see Henseler et al. 2016.

be correlated (Jarvis et al. 2003, p. 203). In fact, high levels of collinearity might even produce an incorrect estimation of outer weights as demonstrated by Hair et al. (2016, p. 142f.). A measure of collinearity is the variance inflation factor (VIF). The VIF is a measure to show how much the variance of the coefficient estimate (i.e., of the formative latent variable) is being inflated by (multi)collinearity (Midi et al. 2010, p. 259). According to Hair et al. (2011, p. 145), each indicator's VIF value should be less than 5.0 to avoid collinearity issues. The resulting VIF values are presented in Table 50. According to the results, LV_PM (2.342) and LV_PS (2.342) have the highest VIF values. Hence, VIF values are uniformly below the threshold value of 5. Thus, the results provide evidence that no collinearity issues arise in the formative measurement models.

Table 50: Collinearity assessment

Formative Indicator	VIF Value
TP_1	1.601
TP_2	1.924
TP_3	1.785
TP_4	2.017
TP_5	2.213
TP_6	2.110
MP_1	2.142
MP_2	2.066
MP_3	2.154
MP_4	2.108
MP_5	2.084
MP_6	1.940
LV_PM	2.342
LV_PS	2.342

4.8.1.2.2 Indicators' Relative Contribution to the Constructs: Indicator Weights & Significance of Weights

Outer weights[53] "are the results of a multiple regression of a construct on its set of indicators. Weights are the primary criterion to assess each indicator's relative importance in formative measurement models" (Hair et al. 2016, p. 323). Outer weights are standardized and can be compared with each other. Each weight represents an indicator's relative contribution to its assigned latent variable. Therefore, a formative specified latent variable is explained in full by its formative indicators (i.e., 100% of the latent variable is explained by its indicators; Hair et al. 2016, p. 145f.). The resulting indicators' weights are presented in Table 51.

A low indicator's outer weight should not be misinterpreted as poor measurement model specification or lead to the elimination of that indicator, since every indicator represents a substantial (non-interchangeable) part of the construct's domain (content validity) (Götz et al. 2010, p. 698). Instead, the question to be investigated is whether formative indicators truly (i.e., if the outer weights significantly differ from zero) contribute to causing ("forming") the latent variable (Hair et al. 2016, p. 146). In PLS-SEM, tests of significance are conducted using the bootstrapping procedure[54]. Examining the significance levels in Table 51 shows that all formative indicators are significant at a 5% level, except TP_4, TP_5, and MP_3.

[53] The terms "outer weight" and "indicator weight" are used interchangeably.

[54] Bootstrapping "is a resampling technique that draws a large number of subsamples from the original data (with replacement) and estimates models for each subsample. It is used to determine standard errors of coefficients to assess their statistical significance without relying on distributional assumptions" (Hair et al. 2016, p. 313). As recommended by Hair, Sarstedt, Ringle, & Mena (2012, p. 429) and Hair et al. (2016, p. 160), the following options were selected using the bootstrapping procedure in SmartPLS 3 (Ringle et al. 2015): the selected number of bootstrap samples was 5000 (subsamples); the no sign change option was chosen to obtain the most conservative results (sign change option); the number of bootstrap cases equalled the number of valid observations (i.e., 517 observations).

Table 51: Indicators' weights and loadings

Formative Construct	Formative Indicator	Outer Weight (Outer Loading)	t-Value
Technical proficiency	TP_1	0.282 (0.751)	4.654***
	TP_2	0.240 (0.783)	3.608***
	TP_3	0.159 (0.661)	2.504*
	TP_4	0.116 (0.693)	1.790
	TP_5	0.142 (0.766)	1.923
	TP_6	0.370 (0.829)	5.817***
Marketing proficiency	MP_1	0.176 (0.735)	2.667**
	MP_2	0.249 (0.727)	3.865***
	MP_3	0.098 (0.752)	1.664
	MP_4	0.216 (0.760)	3.475***
	MP_5	0.297 (0.818)	5.106***
	MP_6	0.266 (0.810)	4.632***
Product competitive advantage	LV_PM	0.481 (0.924)	4.170***
	LV_PS	0.585 (0.949)	5.170***
Note: *Significant for p < .05. (t-value 1.96) **Significant for p < .01. (t-value 2.58) ***Significant for p < .001. (t-value 3.29)			

These non-significant outer weights are not to be interpreted as poor measurement model quality. Instead, Hair et al. (2016, p. 148) recommend to examine the formative indicators' outer loadings[55]. Outer loading represents the absolute contribution of a formative indicator to its latent variable (i.e., the information an indicator provides without considering other indicators assigned to the latent variable). If an indicator's outer weight is not significant but its outer loading is above the threshold value of 0.50, the indicator will be retained and interpreted as absolutely important (Hair et al. 2016, p. 148). Table 51 shows that the values of the indicator loadings for TP_4 (0.693), TP_5 (0.766), and MP_3 (0.752) are all well above the threshold value of 0.50. Thus, the analysis of the formative indicators' relative and absolute contribution as well as their significance provides evidence of an adequate formative measurement model quality.

4.8.1.2.3 Conclusion

The evaluation of the formative measurement models included the analyses of collinearity and the indicators' contribution to their assigned latent variables. A summary of the results is presented in Table 52. The evaluation of the formative measurement models suggests that no collinearity issues arise and each formative indicator contributes to its related latent variable. To conclude, the assessment provides evidence that the measurement quality of the formative measured latent variables (i.e., technical proficiency, marketing proficiency, and product competitive advantage) complies with the requirements of PLS-SEM.

[55] The terms "outer loading" and "indicator loading" are used interchangeably.

Table 52: Formative measurement models evaluation

Formative Construct	Formative Indicator	VIF Value	Outer Weight (Outer Loading)	t-Value
Technical proficiency	TP_1	1.601	0.282 (0.751)	4.654***
	TP_2	1.924	0.240 (0.783)	3.608***
	TP_3	1.785	0.159 (0.661)	2.504*
	TP_4	2.017	0.116 (0.693)	1.790
	TP_5	2.213	0.142 (0.766)	1.923
	TP_6	2.110	0.370 (0.829)	5.817***
Marketing proficiency	MP_1	2.142	0.176 (0.735)	2.667**
	MP_2	2.066	0.249 (0.727)	3.865***
	MP_3	2.154	0.098 (0.752)	1.664
	MP_4	2.108	0.216 (0.760)	3.475***
	MP_5	2.084	0.297 (0.818)	5.106***
	MP_6	1.940	0.266 (0.810)	4.632***
Product competitive advantage	LV_PM	2.342	0.481 (0.924)	4.170***
	LV_PS	2.342	0.585 (0.949)	5.170***

Note: *Significant for $p < .05$. (t-value 1.96) **Significant for $p < .01$. (t-value 2.58) ***Significant for $p < .001$. (t-value 3.29)

4.8.2 Evaluation of the Structural Model

After the successful evaluation of the measurement models (i.e., reliable and valid measurement model estimations), the structural model (i.e., the latent variables and their path relationships) is evaluated (Henseler et al. 2009, p. 303). This includes the study of the model's predictive capabilities and the hypothesized relationships between the latent variables (Hair et al. 2016, p. 191). In particular, the assessment involves testing for collinearity issues, evaluating the significance and relevance of the structural model relationships, the coefficients of determination R^2, the f^2 effect sizes, the predictive relevance Q^2, and the q^2 effect sizes (Hair et al. 2016, p. 190ff.; see Figure 23).

Evaluation of the Structural Model
Collinearity Assessment
Structural Model Path Coefficient
Coefficient of Determination (R^2 Value)
Effect Size f^2
Prediction Relevance Q^2 and Effect Size q^2

Figure 23: Evaluation of the structural model[56]

4.8.2.1 Collinearity Assessment

Collinearity "arises when two variables are highly correlated" (Hair et al. 2016, p. 313). Collinearities between exogenous latent variables can lead to problems, since the estimated path coefficients can become unstable and far from their target values. As a consequence, predictions by the structural model turn out to be of poor quality (Wold et al. 1984, p. 735). As outlined by Dormann et al. (2013, p. 28), collinearity among independent constructs can be considered as a special case of model non-identifiability: if two highly correlated exogenous constructs are both related with an endogenous construct, it will not be possible to identify the "true" predictor without further information. Therefore, Hair et al (2016, p. 209)

[56] Figure adapted from (Hair et al. 2016, p. 106).

advocate examining each exogenous latent variable for collinearity. In particular, the authors suggest that each construct's VIF value should be below the threshold value of 5.0 to avoid collinearity issues (Hair et al. 2011, p. 145; Hair et al. 2016, p. 209). Table 53 shows the VIF values of all combinations of endogenous constructs (represented by the columns) and corresponding exogenous (i.e., predictor) constructs (represented by the rows). The following constructs are assessed for collinearity: technical fit and marketing proficiency as predictors of technical proficiency, technical fit and marketing research fit as predictors of marketing proficiency, technical proficiency as predictor of R&D objective fulfillment, technical fit, marketing research fit, technical proficiency, marketing proficiency, and R&D objective fulfillment as predictors of product competitive advantage. As depicted in Table 53, all values are clearly below the threshold value of 5.0. To conclude, the results demonstrate that collinearity is not an issue in the present structural path model.

Table 53: Collinearity assessment

	1	2	3	4	5	6	7	8	9
1 Technical fit			1.307	1.217		1.550			
2 Marketing research fit				1.227		1.473			
3 Technical proficiency					1.016	2.539			
4 Marketing proficiency			1.319			2.272			
5 R&D objective fulfillment						1.333			
6 Product competitive advantage									
7 Number project partners			1.317	1.322	1.317	1.325			
8 Project duration			1.247	1.247	1.250	1.258			
9 Size project team			1.425	1.422	1.407	1.433			

4.8.2.2 Structural Model Path Coefficients

Path coefficients "are estimated path relationships in the structural model (i.e., between the constructs in the model)" (Hair et al. 2016, p. 324) and their estimation can be considered as the basis for hypothesis testing (Kock 2014, p. 3). In the present study, each path coefficient refers either to a hypothesis or to a

control path to account for effects not suggested in the hypotheses. Tables 54 to 56 display the standardized path coefficients and respective t-values. The bootstrapping procedure was used to assess the significance of path coefficients.[57] Path estimation indicates that technical fit has no direct effect on product competitive advantage ($\beta = 0.001$, n.s.[58]), rejecting hypothesis H1. Likewise, marketing research fit does not enhance product competitive advantage ($\beta = -0.052$, n.s.), rejecting hypothesis H2. Confirming hypothesis H3, technical fit positively affects technical proficiency ($\beta = 0.279$, $p < 0.001$). Technical fit also increases marketing proficiency ($\beta = 0.321$, $p < 0.001$), supporting hypothesis H4. Furthermore, marketing research fit enhances marketing proficiency ($\beta = 0.371$, $p < 0.001$), supporting hypothesis H5. Confirming hypothesis H6, marketing proficiency directly affects technical proficiency ($\beta = 0.578$, $p < 0.001$). Supporting hypothesis H7, marketing proficiency positively affects product competitive advantage ($\beta = 0.293$, $p < 0.001$). Technical proficiency has no direct effect on product competitive advantage ($\beta = 0.131$, n.s.), rejecting hypothesis H8. Confirming hypothesis H9, technical proficiency directly affects R&D objective fulfillment ($\beta = 0.477$, $p < 0.001$). Supporting the last hypothesis H10, R&D objective fulfillment enhances product competitive advantage ($\beta = 0.307$, $p < 0.001$). Regarding the control paths, only project duration has a significant - however extremely weak - direct effect on product competitive advantage ($\beta = 0.096$, $p < 0.01$).

[57] As recommended by Hair, Sarstedt, Ringle, & Mena (2012, p. 429) and Hair et al. (2016, p. 160), the following options were selected using the bootstrapping procedure in SmartPLS 3 (Ringle et al. 2015): the selected number of bootstrap samples was 5000 (subsamples); the no sign change option was chosen to obtain the most conservative results (sign change option); the number of bootstrap cases equalled the number of valid observations (i.e., 517 observations).

[58] n.s. = not significant.

Table 54: Standardized path coefficients and significances (I)

Hypothesized Path	Hypothesis	Path Coefficient	t-Value	Supported
Technical fit → Product competitive advantage	H1	0.001	0.021	No
Marketing research fit → Product competitive advantage	H2	-0.052	1.071	No
Technical fit → Technical proficiency	H3	0.279	7.211***	Yes
Technical fit → Marketing proficiency	H4	0.321	6.968***	Yes
Marketing research fit → Marketing proficiency	H5	0.371	8.295***	Yes
Marketing proficiency → Technical proficiency	H6	0.578	15.888***	Yes
Marketing proficiency → Product competitive advantage	H7	0.293	4.541***	Yes
Technical proficiency → Product competitive advantage	H8	0.131	1.938	No
Technical proficiency → R&D objective fulfillment	H9	0.477	11.486***	Yes
R&D objective fulfillment → Product competitive advantage	H10	0.307	5.920***	Yes
Notes: β = standardized path coefficient; *Significant for $p < 0.05$ (t-value 1.96); **Significant for $p < .01$ (t-value 2.58); ***Significant for $p < .001$ (t-value 3.29).				

Table 55: Standardized path coefficients and significances (II)

Hypothesized Path	Hypothesis	Path Coefficient	t-Value	Supported
Number project partners → technical proficiency	Control Path	-0.033	1.086	
Number project partners → Marketing Proficiency	Control Path	-0.017	0.455	
Number project partners → R&D objective fulfillment	Control Path	-0.026	0.588	
Number project partners → Product competitive advantage	Control Path	-0.047	1.104	
Project duration → Technical proficiency	Control Path	0.057	1.660	
Project duration → Marketing proficiency	Control Path	-0.002	0.042	
Project duration → R&D objective fulfillment	Control Path	-0.049	1.151	
Project duration → Product competitive advantage	Control Path	0.096	2.727**	
Size project team→ Technical proficiency	Control Path	-0.025	0.723	
Size project team → Marketing proficiency	Control Path	0.074	1.700	
Size project team→ R&D objective fulfillment	Control Path	-0.011	0.229	
Notes: β = standardized path coefficient; *Significant for p < 0.05 (t-value 1.96); **Significant for p < .01 (t-value 2.58); ***Significant for p < .001 (t-value 3.29).				

Table 56: Standardized path coefficients and significances (III)

Hypothesized Path	Hypothesis	Path Coefficient	t-Value	Supported
Size project team → Product competitive advantage	Control Path	-0.050	0.723	
Notes: β = standardized path coefficient; *Significant for p < 0.05 (t-value 1.96); **Significant for p < .01 (t-value 2.58); ***Significant for p < .001 (t-value 3.29).				

Figure 24 illustrates the research model including the respective path coefficients.

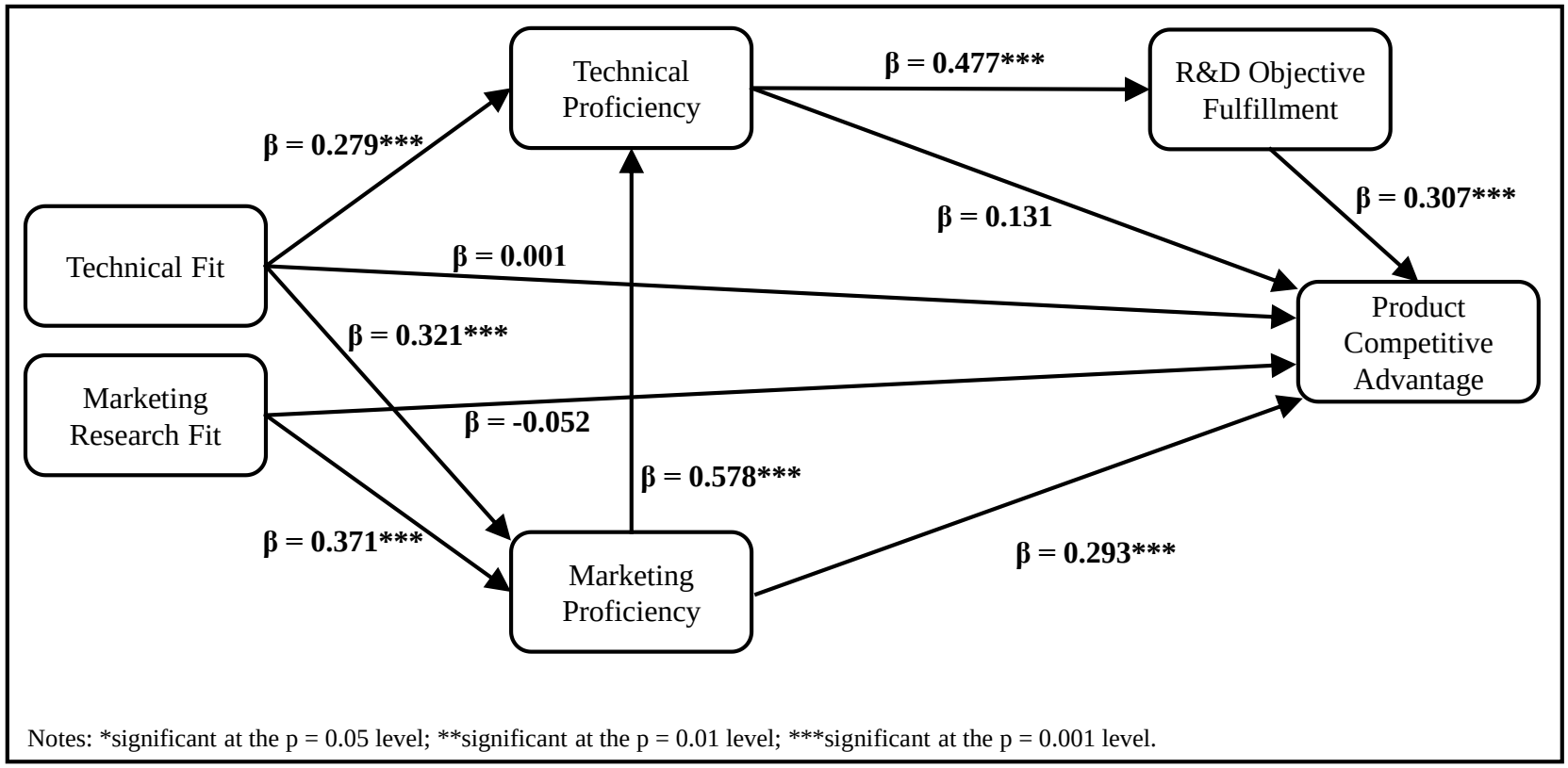

Figure 24: Research model including path coefficients and path significances

In addition to examining one latent variable's direct effect on another, Hair et al. (2016, p. 197f.) recommend investigating its indirect effects through one or more mediating latent variables. The sum of direct and indirect effects represents the total effect of a particular construct on a target construct. The interpretation of total effects is advised for studies aiming to explore the differential influence of several driver variables on a target variable through one or more mediating variables (Hair et al. 2016, p. 197f.).

Table 57 displays the total effect values and respective t-values. The bootstrapping procedure was used to assess the significance of path coefficients.[59] First, this procedure allows exploring whether the driver construct of technical fit (ultimately) influences the key target construct of product competitive advantage via the constructs of technical proficiency, marketing proficiency, and R&D objective fulfillment. Though the driver construct has no significant direct effect on the target construct, results demonstrate that technical fit ultimately has an impact on product competitive advantage (0.224, $p < 0.001$). Second, it can be investigated whether the driver construct of marketing research fit (ultimately) influences the key target construct of product competitive advantage via the constructs of technical proficiency, marketing proficiency, and R&D objective fulfillment. It can again be found that though the driver construct has no significant direct effect on the target construct, the results demonstrate that marketing research fit ultimately has an impact on product competitive advantage (0.116, $p < 0.05$). Finally, and with regard to the key target variable product competitive advantage, it becomes apparent that among the four driver constructs, marketing proficiency has the strongest total effect on product competitive advantage (0.454, $p < 0.001$), followed by technical proficiency (0.278, $p < 0.001$).

[59] As recommended by Hair, Sarstedt, Ringle, & Mena (2012, p. 429) and Hair et al. (2016, p. 160), the following options were selected using the bootstrapping procedure in SmartPLS 3 (Ringle et al. 2015): the selected number of bootstrap samples was 5000 (subsamples); the no sign change option was chosen to obtain the most conservative results (sign change option); the number of bootstrap cases equalled the number of valid observations (i.e., 517 observations).

Table 57: Significance testing results of the total effects

Path	Total Effect	t-value
Technical fit → Product competitive advantage	0.224	4.293***
Marketing research fit → Product competitive advantage	0.116	2.446*
Marketing proficiency → Product competitive advantage	0.454	8.219***
Technical proficiency → Product competitive advantage	0.278	4.220***
Notes: *Significant for p < 0.05 (t-value 1.96); **Significant for p < .01 (t-value 2.58); ***Significant for p < .001 (t-value 3.29).		

4.8.2.3 Coefficient of Determination (R^2 Value)

The predominant criterion for the evaluation of predictive power of PLS-SEM is the coefficient of determination (R^2) (Hair, Sarstedt, Ringle, & Mena 2012, p. 426; Sarstedt et al. 2014, p. 156). The coefficient of determination is computed as the squared correlation between an endogenous latent variable's actual and predicted value and therefore "a measure of the proportion of an endogenous construct's variance that is explained by its predictor constructs" (Hair et al. 2016, p. 313). In other words, the R^2 value embodies the exogenous constructs' combined effects on the endogenous construct (Hair et al. 2016, p. 198).

As a prediction oriented-approach, the objective of PLS-SEM is to maximize the R^2 values of the endogenous constructs in the structural path model (Hair et al. 2016, p. 209). R^2 values vary between 0 and 1, with higher values indicating a larger percentage of variance explained (Götz et al. 2010, p. 701). However, there is no generally valid threshold value, since the R^2 values depend on a large extent on the research context (e.g., highly exploratory research), the role of the latent variables (e.g., mediator or target variable), and model complexity (Hair, Sarstedt, Ringle, & Mena 2012, p. 430; Hair et al. 2016, p.

198f.). In the present study and depicted in Table 58, technical proficiency has the highest R^2 value (0.570), followed by marketing proficiency (0.354), product competitive advantage (0.347), and R&D objective fulfillment (0.230).

Table 58: Coefficient of determination (R^2 value)

	R^2 value
Technical proficiency	0.570
Marketing proficiency	0.354
R&D objective fulfillment	0.230
Product competitive advantage	0.347

4.8.2.4 Effect Size f^2

While the coefficient of determination indicates the explained proportion of an endogenous construct's variance, the effect size f^2 can be applied to evaluate whether an exogenous latent variable exerts a significant influence (effect) on an endogenous latent variable (Weiber/Mühlhaus 2014, p. 328). The f^2 effect size is defined as "a measure used to assess the relative impact of a predictor construct on an endogenous construct" (Hair et al. 2016, p. 317).

The effect size f^2 of an endogenous construct demonstrates how much the R^2 value (of that endogenous construct) changes when an associated exogenous construct is not used for estimating the coefficient of determination (Weiber/Mühlhaus 2014, p. 328). To be more precise, the change in the R^2 value of the endogenous construct is computed by estimating the path model twice: the first time with the associated exogenous construct, and the second time without the associated exogenous construct (Götz et al. 2010, p. 702). Chin (1998b, p.

317) classifies effect size f^2 values of 0.02, 0.15, 0.35 as the exogenous construct's small, medium, or large effects (respectively) on a particular endogenous construct (Götz et al. 2010, p. 702). Following the guidelines of Hair et al. (2016, p. 201f.), an effect size f^2 value of less than 0.02 indicates that there is no relative impact of a predictor construct on an endogenous construct.

Table 59 shows the f^2 values for all combinations of endogenous constructs (represented by the columns) and corresponding exogenous (i.e., predictor) constructs (represented by the rows). Technical fit has a small to an almost medium effect size of 0.138 on technical proficiency and of 0.131 on marketing proficiency. In correspondence with the identified non-significant relationship of hypothesis H1, technical fit has no effect on product competitive advantage (0.000). Marketing research fit has a medium effect size of 0.174 on marketing proficiency but no effect on product competitive advantage (0.003). Again, the latter supports the results of hypothesis H2, which revealed a non-significant relationship between these constructs. Technical proficiency has a medium effect size of 0.290 on R&D objective fulfillment but no effect on product competitive advantage (0.010). The latter is in accordance with the results of hypothesis H8 that there was no significant relationship between these variables. Marketing proficiency has a large effect size of 0.589 on technical proficiency and a small effect size of 0.058 on product competitive advantage. Finally, R&D objective fulfillment has a small effect size of 0.108 on product competitive advantage.

Table 59: Effect size f^2

	1	2	3	4	5	6	7	8	9
1 Technical fit			0.138	0.131		0.000			
2 Marketing research fit				0.174		0.003			
3 Technical proficiency					0.290	0.010			
4 Marketing proficiency			0.589			0.058			
5 R&D objective fulfillment						0.108			
6 Product competitive advantage									
7 Number project partners			0.002	0.000	0.001	0.003			
8 Project duration			0.006	0.000	0.003	0.011			
9 Size project team			0.001	0.006	0.000	0.003			

4.8.2.5 Prediction Relevance Q^2 and Effect Size q^2

The Stone-Geisser criterion Q^2 (Geisser 1974; Stone 1974) can be applied to assess the predictive relevance of an endogenous construct that has a reflective measurement specification (Chin 1998b, p. 317f.). This measure evaluates whether a model "accurately predicts data not used in the estimation of model

parameters" (Hair et al. 2016, p. 325) by means of the blindfolding procedure. By applying this technique, part of the original data matrix is systematically assumed to be missing during parameter estimation. Then, the obtained parameter values are used to predict the missing raw data (Weiber/Mühlhaus 2014, p. 329). Thus, the Q^2 value is a measure of out-of-sample predictive power or predictive relevance (Hair et al. 2016, p. 325). A Q^2 value larger than 0 represents predictive relevance of the model, whereas a Q^2 value smaller than 0 implies a lack of predictive relevance (Chin 1998b, p. 318; Henseler et al. 2009, p. 303). The only endogenous construct in the model that has a reflective measurement specification is R&D objective fulfillment. This construct has a Q^2 value of 0.188, which supports the model's predictive relevance. However, the Q^2 value only implies that the endogenous latent variable (i.e., R&D objective fulfillment) can be predicted but does not allow evaluating the quality of the prediction (Sarstedt et al. 2014, p. 156). Therefore, the effect size q^2 is applied to assess "the relative predictive relevance of a predictor construct on an endogenous construct" (Hair et al. 2016, p. 325).

In analogy to the effect size f^2, the change in the q^2 value of the endogenous construct is calculated by estimating the path model twice: the first time with the associated exogenous construct, and the second time without the associated exogenous construct (Weiber/Mühlhaus 2014, p. 330). In the proposed model, technical proficiency is the only predictor variable of R&D objective fulfillment. The q^2 effect size of technical proficiency on R&D objective fulfillment is 0.230, which implies a moderate predictive relevance of the predictor variable on the endogenous construct (Hair, Sarstedt, Ringle, & Mena 2012, p. 430).

4.8.2.6 Conclusion

In correspondence with Hair et al. (2016, p. 190ff.), the evaluation of the structural model included an initial investigation of collinearity issues, the assessment of the significance and relevance of the structural model relationships, the level of the coefficient of determination R^2, the f^2 effect size, the predictive relevance Q^2, and the q^2 effect size. Data analysis showed that collinearity was no concern, all endogenous variables were well explained (average $R^2 = 0.38$), and

the model had predictive relevance. Path estimation indicated that all hypotheses were supported, except hypotheses H1, H2, and H8. In sum, the assessment demonstrated that marketing proficiency had the strongest total effect on product competitive advantage, followed by R&D objective fulfillment, technical proficiency, technical fit, and marketing fit.

4.8.3 Additional Analysis

4.8.3.1 Mediation Analysis

PLS-SEM is a powerful statistical analysis technique for testing hypotheses in complex models which are of exploratory nature (Reinartz et al. 2009; Dijkstra 2010; Hair, Sarstedt, Pieper, & Ringle 2012; Hair, Sarstedt, Ringle, & Mena 2012; Ringle et al. 2012; Hair et al. 2016; Nitzl et al. 2016). However, in complex models, it is important to ensure that effects that do not directly reveal themselves are not neglected. Not only direct effects have to be examined but also potential indirect effects (Hair et al. 2016, p. 227ff.). The consideration and investigation of indirect effects are necessary for a proper interpretation of the empirical results. Otherwise, there is a chance that certain interrelationships inherent in research data will not be recognized, and therefore, not be taken into account in the evaluation of the research model (Nitzl et al. 2016, p. 1849). In particular, a mediation analysis is to be conducted in order to capture the whole range of interrelationships between a model's constructs (Hair et al. 2016, p. 227ff.). "Only when the possible mediation is theoretically taken into account and also empirically tested can the nature of the cause-effect relationship be fully and accurately understood" (Hair et al. 2016, p. 232).

Mediation is "one way that a researcher can explain the process or mechanism by which one variable affects another" (MacKinnon et al. 2007, p. 594). Mediation analysis focuses on a sequence of relationships in which an independent variable influences a mediation variable, which then influences a dependent variable (Nitzl et al. 2016, p. 1850). Thus, a third variable exists in mediation, which takes on an intermediate role in the relationship between the independent and dependent variables (Hair et al. 2016, p. 227f.). "Technically speaking, the effect of the independent variable X on the dependent variable Y is

mediated by a third variable, M, called the mediating variable or mediator" (Nitzl et al. 2016, p. 1851; see Figure 25).

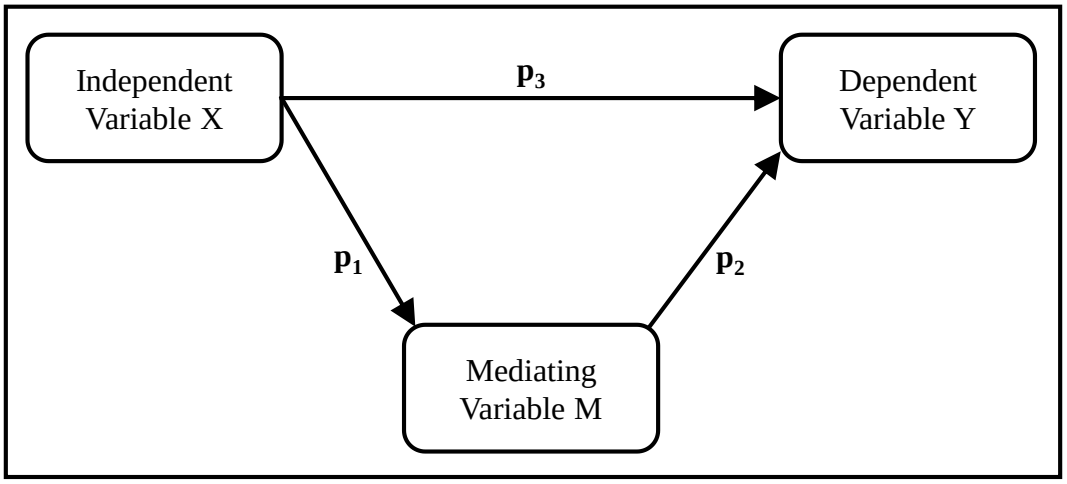

Figure 25: General mediation model[60]

In the conceptual development of the research model of this thesis, it was assumed that marketing proficiency partially mediates the effect of technical fit on technical proficiency, R&D objective fulfillment partially mediates the effect of technical proficiency on product competitive advantage, marketing proficiency partially mediates the effect of marketing research fit on product competitive advantage, technical proficiency partially mediates the effect of technical fit on product competitive advantage, and finally technical proficiency partially mediates the effect of marketing proficiency on product competitive advantage (see Section 3.2).

Figure 26 illustrates the guidelines for conducting a mediation analysis according to Zhao et al. (2010), Hair et al. (2016), as well as Nitzl et al. (2016). In the process of the mediation analysis, the bootstrapping procedure (5,000 replications) is applied to assess the significance of the direct and indirect effects (Preacher/Hayes 2004, p. 717ff.; Preacher/Hayes 2008, p. 879ff.; Hair et al. 2016, p. 228ff.).

[60] Figure adapted from Nitzl et al. (2016, p. 1851).

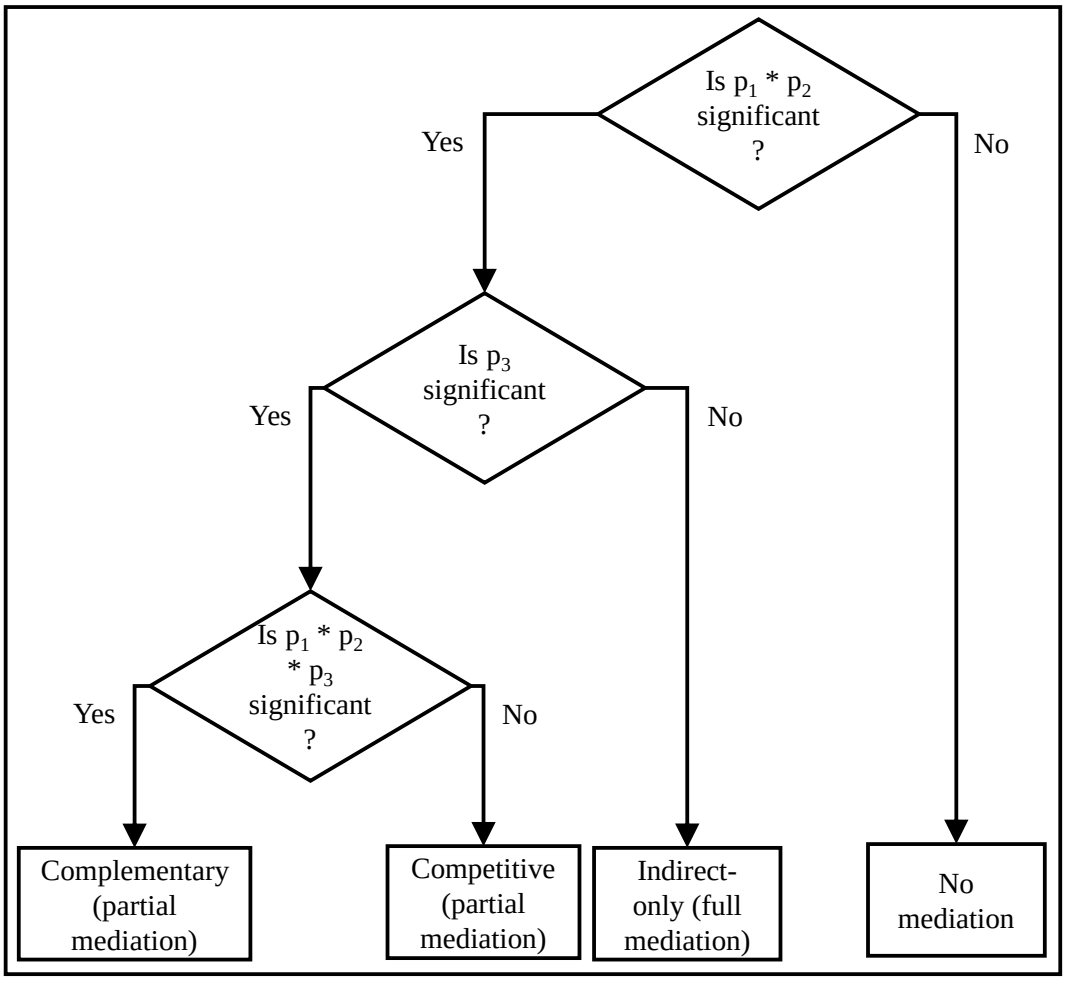

Figure 26: Mediator analysis procedure[61]

The first step of the mediator analysis involves determining the significance of the indirect effect (i.e., $p_1 * p_2$) of the relationship under investigation (Zhao et al. 2010, p. 201; Hair et al. 2016, p. 233; Nitzl et al. 2016, p. 1853). "The one and only requirement to demonstrate mediation is a significant indirect effect" (Zhao et al. 2010, p. 200). Therefore, two of the hypothesized relationships in the research model of this thesis inherent no mediation effects: technical proficiency does not mediate the effect of a) technical fit on product competitive advantage and b) of marketing proficiency on product competitive advantage.[62] The underlying reason is that the relationship between technical proficiency and product competitive advantage is not significant at a level of 0.05 (t = 1.938; see Section 4.8.2.2). It can be concluded that technical proficiency

[61] Figure adapted from Zhao et al. (2010, p. 201), Hair et al. (2016, p. 233), and Nitzl et al. (2016, p. 1853).

[62] Please note that the remaining hypothesized relationships in the research model which inherent mediation effects are discussed later in this section.

does not function as a mediator in any of the relationships in the research model. The remaining four hypothesized relationships in the research model of this thesis inherent mediation effects and will be discussed in detail after this brief description of the mediator analysis procedure.

The second step of the analysis determines the type of mediation (Zhao et al. 2010, p. 201; Hair et al. 2016, p. 233; Nitzl et al. 2016, p. 1853). A relationship which has already been confirmed to hold a significant indirect effect is now tested for the significance of a direct effect (p_3) between the independent variable and the dependent variable (see Figure 25). If the direct effect is not significant, the relationship under investigation will be characterized as full-mediation. The effect from the independent variable to the dependent variable is completely passed via the mediating variable (Zhao et al. 2010, p. 200; Hair et al. 2016, p. 234; Nitzl et al. 2016, p. 1855). "Technically speaking, the variable X extracts his influence only under a certain condition of M on Y" (Nitzl et al. 2016, p. 1855). When classifying a mediation as "full-mediation", the role of the sample size has also to be considered (Rucker et al. 2011, p. 364f.; Nitzl et al. 2016, p. 1855). According to Rucker et al. (2011, p. 364), "[t]he smaller the sample, the more likely mediation (when present) is to be labeled full as opposed to partial, because [the direct effect] is more easily rendered nonsignificant." However, the cases which are included in the empirical analysis of this thesis (i.e., the sample size) are 517, and shall, therefore, be regarded as a sufficient sample size (see Section 4.5; for a discussion on sample size in the context of the PLS-SEM algorithm, see Henseler et al. 2016, p. 8).[63]

When the direct effect is significant, the relationship under investigation is characterized as partial mediation, whereby it is distinguished between complementary partial mediation and competitive partial mediation (Zhao et al. 2010, p. 200f.; Hair et al. 2016, p. 234; Nitzl et al. 2016, p. 1856).

[63] For a simple mediation model such as that shown in Figure 24, "the necessary sample size is quite low, starting with 30 cases to detect strong effects, which is often the case in the context of experimental research (small sample per group and analyzing strong effects). Notwithstanding, a medium and small effect size would require a sample of 66 and 481 cases, respectively." (Nitzl et al. 2016, p. 1855).

In case of a complementary partial mediation, the significant indirect effect and the significant direct effect point in the same direction (Zhao et al. 2010, p. 200f.; Hair et al. 2016, p. 234; Nitzl et al. 2016, p. 1856). The product of the indirect effect and the direct effect (i.e., $p_1*p_2*p_3$) is positive (Hair et al. 2016, p. 234). The mediator variable explains or falsifies the relationship between independent and dependent variables (Nitzl et al. 2016, p. 1856). Technically speaking, "a portion of the effect of X on Y is mediated through M, whereas X still explains a portion of Y that is independent of M" (Nitzl et al. 2016, p. 1856).

In case of a competitive partial mediation, the significant indirect effect and the significant direct effect point in opposite directions (Zhao et al. 2010, p. 200f.; Hair et al. 2016, p. 234; Nitzl et al. 2016, p. 1856). The product of the indirect effect and the direct effect (i.e., $p_1*p_2*p_3$) is negative (Hair et al. 2016, p. 234). Again, "a portion of the effect of X on Y is mediated through M, whereas X still explains a portion of Y that is independent of M" (Nitzl et al. 2016, p. 1856). The mediator variable reduces or increases the magnitude of the relationship between independent and dependent variables (Nitzl et al. 2016, p. 1856).[64]

The remaining relationships of the research model are now analyzed for mediating effects in accordance with the above-depicted procedure.

The first relationship under investigation is the influence of technical fit on technical proficiency and the mediating role of marketing proficiency (see Figure 27).

[64] For more details and an example regarding competitive partial mediation, it is recommended to see Nitzl et al. (2016, p. 1856).

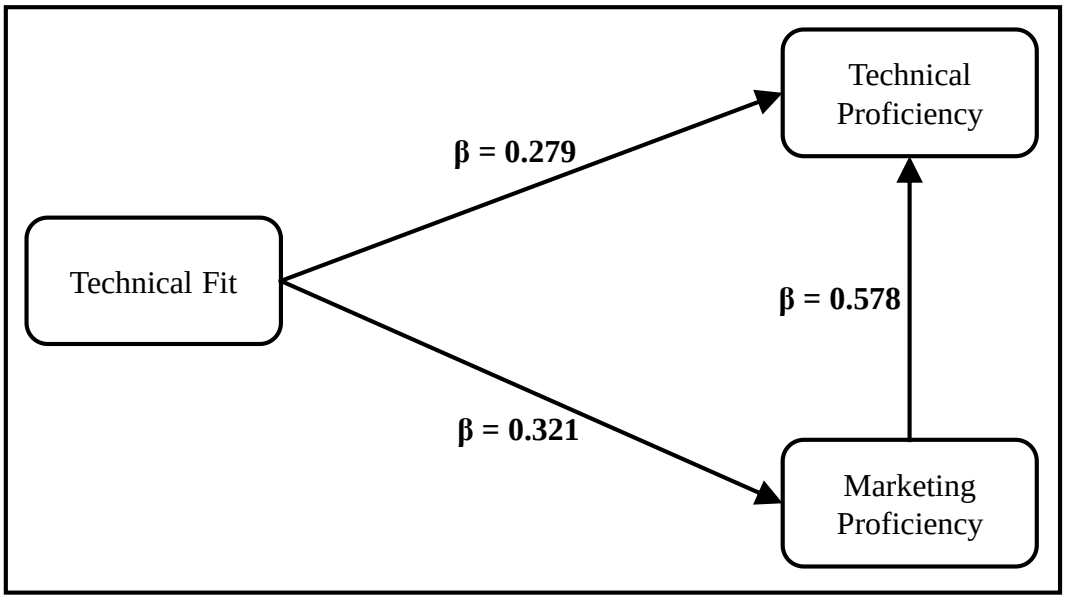

Figure 27: Relationship between technical fit and technical proficiency and the mediating role of marketing proficiency

The empirical t-value of the indirect effect (0.186) for the technical fit → technical proficiency relationship is 6.952, yielding a p-value of <0.001 (i.e., the indirect effect is significant). As shown in Table 60, the direct effect from technical fit on technical proficiency is 0.279 and statistically significant (t = 7.211; p = <0.001). In correspondence with the mediation analysis presented in Figure 25, it can be concluded that marketing proficiency partially mediates the relationship between technical fit and technical proficiency. To identify the type of partial mediation, the product of the direct effect and the indirect effect is calculated. The sign of their product is positive (i.e., 0.279 * 0.186 = 0.051894), therefore, it can be concluded that marketing proficiency represents complementary mediation of the relationship from technical fit to technical proficiency. In sum, higher levels of technical fit increase technical proficiency directly but also increase marketing proficiency, which in turn leads to higher levels of technical proficiency. Hence, some of the effect of technical fit on technical proficiency is explained by marketing proficiency.

The results of the mediation analysis support the notion of information-processing theory (e.g., Tushman/Nadler 1978; Daft/Lengel 1986; Sinkula 1994; Song et al. 2005), which asserts that the information-processing capabilities (e.g., the ability to gather, interpret, and utilize technological information) must fit the information-processing requirements facing an R&D project in order to

proficiently conduct the various technical and marketing activities (Tushman/Nadler 1978). With regard to the mediating role of marketing proficiency, marketing-related activities provide data, which are transformed into information that guide the direction of the development process and foster the proficient execution of technical activities.

Table 60: Significances of the direct and indirect effects in the relationship between technical fit and technical proficiency

	Direct Effect	t-Value	Significant for p	Indirect Effect	t-Value	Significant for p
Technical fit → Technical proficiency	0.279	7.211	<0.001	0.186	6.952	<0.001

The second relationship under investigation is the influence of technical proficiency on product competitive advantage and the mediating role of R&D objective fulfillment (see Figure 28).

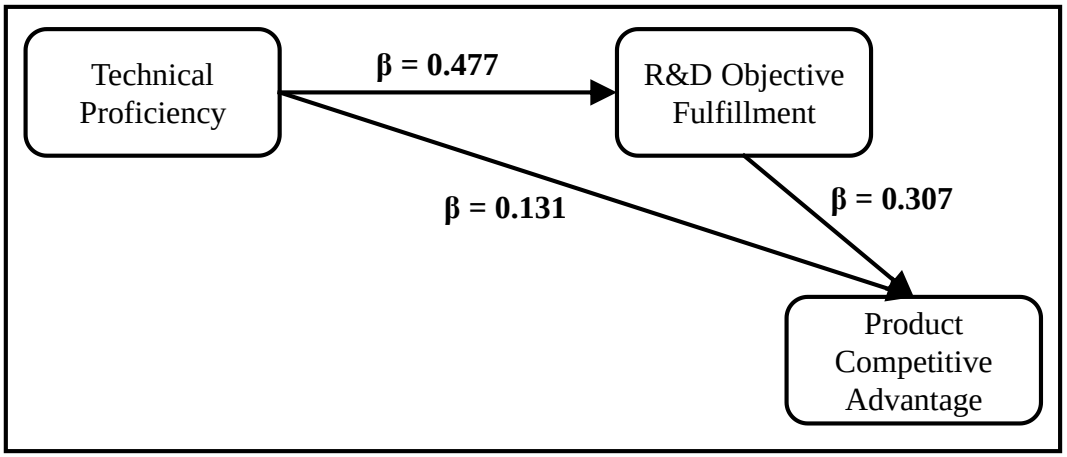

Figure 28: Relationship between technical proficiency and product competitive advantage and the mediating role of R&D objective fulfillment

The empirical t-value of the indirect effect (0.146) for the technical proficiency → product competitive advantage relationship is 5.185, yielding a p-value of <0.001 (i.e., the indirect effect is significant). As shown in Table 61, the direct effect from technical proficiency on product competitive advantage is 0.131 and statistically non-significant (t = 1.938; n.s.). In correspondence with the mediation analysis presented in Figure 25, it can be concluded that R&D objective

fulfillment fully mediates the relationship between technical proficiency and product competitive advantage.

In sum, the analysis provides empirical support for the mediating role of R&D objective fulfillment in the research model of this thesis. In particular, R&D objective fulfillment represents a mechanism that underlies the relationship between technical proficiency and product competitive advantage. High levels of technical proficiency lead to high levels of R&D objective fulfillment, and high levels of R&D objective fulfillment lead to product competitive advantage.

The results of the mediation analysis demonstrate the importance of considering the specific characteristics of the biotechnology industry, which involves highly experimental research (De Luca et al. 2010, p. 308). R&D projects in the biotechnology industry inherent uncertainty with regard to their potential outcome (Rothaermel/Deeds 2004, p. 208f.). However, it is expected that the proficient execution of technical activities (e.g., prototype testing) generates data which is interpreted and drawn conclusions from (Egelhoff 1991, p. 342f.). This gained information serves as new input for the iterative process of technical R&D activities. Therefore - as it was hypothesized and eventually supported by the data - the more proficient technical activities are executed, the more valuable information will be obtained that will support the product development process and thus the fulfilment of the initial R&D objective. Since research goals are expected to be based on user preferences, market trends and a clear understanding of “appeal” characteristics that would differentiate the product, the fulfillment of the R&D objective is shown to be positively related to the achievement of a product competitive advantage (i.e., a product that is superior to competitive offerings and meaningful to target users).

Table 61: Significances of the direct and indirect effects in the relationship between technical proficiency and product competitive advantage

	Direct Effect	t-Value	Significant for p	Indirect Effect	t-Value	Significant for p
Technical proficiency → Product competitive advantage	0.131	1.938	n.s.	0.146	5.185	<0.001

The third relationship under investigation is the influence of marketing research fit on product competitive advantage and the mediating role of marketing proficiency (see Figure 29).

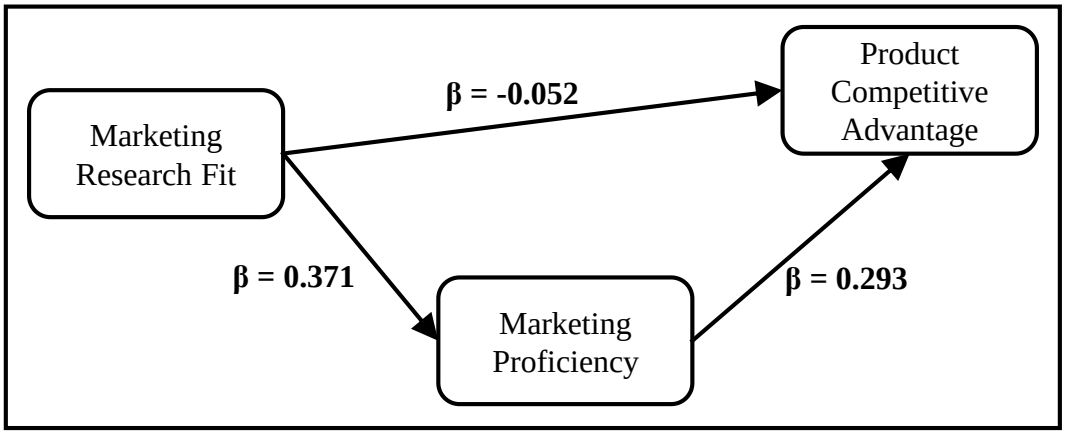

Figure 29: Relationship between marketing research fit and product competitive advantage and the mediating role of marketing proficiency

The empirical t-value of the indirect effect (0.109) for the marketing research fit → product competitive advantage relationship is 4.134, yielding a p-value of <0.001 (i.e., the indirect effect is significant). As shown in Table 62, the direct effect from marketing research fit on product competitive advantage is -0.052 and statistically non-significant (t = 1.071; n.s.). In correspondence with the mediation analysis presented in Figure 25, it can be concluded that marketing proficiency fully mediates the relationship between marketing research fit and product competitive advantage. In sum, the analysis provides empirical support for the mediating role of marketing proficiency in the research model of this thesis. In particular, marketing proficiency represents a mechanism that underlies the relationship between marketing research fit and product competitive advantage. High levels of marketing research fit lead to high levels of marketing

proficiency, and high levels of marketing proficiency lead to product competitive advantage.

The results of the mediation analysis support the notion of Day/Wensley (1988, p. 7), who argue that superior resources and skills are not automatically converted into competitive advantages. It is shown that the relationship between an R&D project's fit with the available marketing research skills and resources and product competitive advantage is mediated by the proficient execution of marketing activities (e.g., market research) which characterize the cooperative R&D project (Song/Parry 1997a, p. 3).

Table 62: Significances of the direct and indirect effects in the relationship between marketing research fit and product competitive advantage

	Direct Effect	t-Value	Significant for p	Indirect Effect	t-Value	Significant for p
Marketing research fit → Product competitive advantage	-0.052	1.071	n.s.	0.109	4.134	<0.001

The fourth and final relationship under investigation is the influence of technical fit on product competitive advantage and the mediating role of marketing proficiency (see Figure 30).

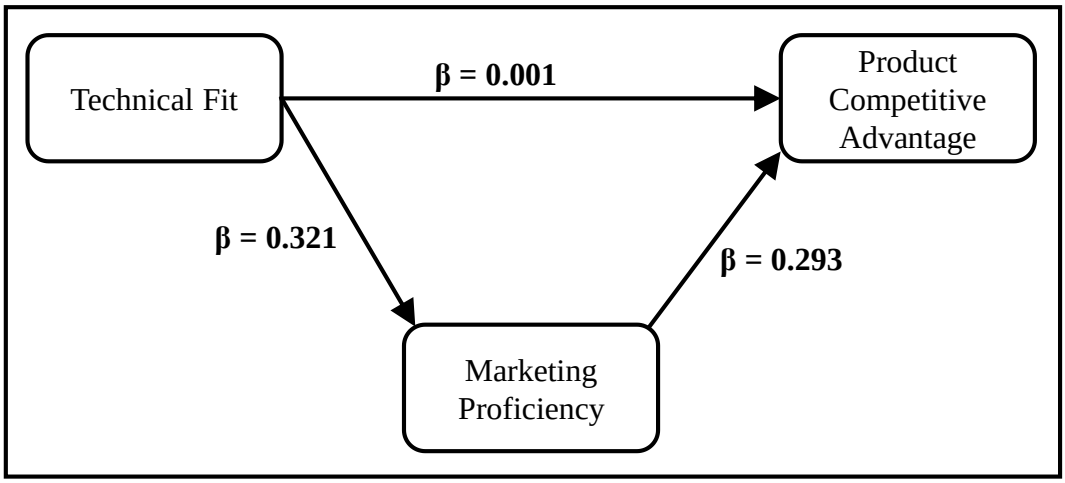

Figure 30: Relationship between technical fit and product competitive advantage and the mediating role of marketing proficiency

The empirical t-value of the indirect effect (0.094) for the technical fit → product competitive advantage relationship is 3.738, yielding a p-value of <0.001 (i.e., the indirect effect is significant). As shown in Table 63, the direct effect from technical fit on product competitive advantage is 0.001 and statistically non-significant (t = 0.021; n.s.). In correspondence with the mediation analysis presented in Figure 25, it can be concluded that marketing proficiency fully mediates the relationship between technical fit and product competitive advantage. In sum, the analysis again demonstrates empirical support for the mediating role of marketing proficiency in the research model of this thesis. In particular, marketing proficiency represents a mechanism that underlies the relationship between technical fit and product competitive advantage. High levels of technical fit lead to high levels of marketing proficiency and high levels of marketing proficiency lead to product competitive advantage.

The results of the mediation analysis demonstrate once more that superior resources and skills are not directly tied to the achievement of competitive advantages (Day/Wensley 1988, p. 7). Instead, it is the competent execution of marketing activities in cooperative R&D projects (e.g., market research) that mediates the relationship between an R&D project's fit with the available technical skills and resources and product competitive advantage.

Table 63: Significances of the direct and indirect effects in the relationship between technical fit and product competitive advantage

	Direct Effect	t-Value	Significant for p	Indirect Effect	t-Value	Significant for p
Technical fit → Product competitive advantage	0.001	0.021	n.s.	0.094	3.738	<0.001

4.8.3.2 Comparison of Effects in Subsamples

PLS-SEM applications typically analyze the entire data set, implicitly considering that the data used originate from a single homogeneous population (Hair et al. 2016, p. 290). However, one might argue that the assumption of homogeneous data characteristics does not hold for the data set of this thesis because of the

diverse and interdisciplinary nature of biotechnology. For instance, R&D in the biotechnological area of human health and medicine is heavily science-based and considered to be tedious, risky and expensive (Schüler 2016, p. 167ff). There is actually no other product that is as complex to develop as drugs, especially due to extensive human testing studies and very strict market approval requirements (Schüler 2016, p. 167). Hence, the proposed relationships (i.e., path coefficients and their significances) in the research model (see Section 3.2) might differ between the biotechnological area of human health/medicine and other biotechnological areas of activity. Disregarding potential data heterogeneity may threaten the validity of PLS-SEM results and entail misleading conclusions (Sarstedt et al. 2009, p. 185ff.; Sarstedt et al. 2011, p. 197; Hair et al. 2016, p. 290).

Therefore, a multigroup analysis to compare the hypothesized paths in the research model and to detect potential differences across data groups is conducted. A multigroup analysis can be considered as a special case of moderation analysis (Sarstedt et al. 2011, p. 198; Hair et al. 2016, p. 322). A moderation occurs when a (moderator) variable ‘‘affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable’’ (Baron/Kenny 1986, p. 1174). In multigroup analyses, the moderator variable is categorical and potentially affects all the relationships in the research model (Henseler/Chin 2010, p. 83; Hair et al. 2016, p. 322). In particular, it is tested whether parameter estimates differ significantly between groups (Sarsted et al. 2011, p. 198; Hair et al. 2016, p. 322).

In the following multigroup analysis, two groups or subsamples are under investigation: a) the subsample of responses regarding cooperative R&D projects in the biotechnological area of human health and medicine (HHM subsample), and b) the subsample of responses regarding cooperative R&D projects in other biotechnological areas of activity (non-HHM subsample). The latter group involves responses concerning the biotechnological areas of industrial biotechnology, agricultural biotechnology, non-specific applications, not (yet) assignable applications, and animal health (see Section 4.5). As described in Section 4.5, 517 usable questionnaires were returned in total. The HHM subsample includes 295 cases, and the non-HHM subsample contains 222 cases.

The first prerequisite when comparing model estimates across subsamples is to verify that construct measures are invariant across the two groups under investigation (see Section 4.8.3.2.1). The second prerequisite is that the quality of the measurement models complies with the requirements of PLS-SEM for both subsamples (see Section 4.8.3.2.2). Eventually, the multigroup analysis can be conducted (see Section 4.8.3.2.3).

4.8.3.2.1 Measurement Invariance Tests

When conducting comparisons of model estimation results across different groups of respondents, the first step involves the assessment of measurement invariance (Henseler et al. 2016). Following the definition of Henseler et al. (2016, p. 406), measurement invariance is concerned with "whether or not, under different conditions of observing and studying phenomena, measurement operations yield measures of the same attribute" (Horn/McArdle 1992, p. 117). By establishing measurement invariance, it is ensured that (possibly different) group-specific model estimates (e.g., different relationships between variables) "do not result from distinctive content and the meanings of the latent variables across groups" (Henseler et al. 2016, p. 409). In other words, it is ensured that potential variations in the relationships between constructs do not result - for instance - from different understandings of R&D activities or product competitive advantage between respondents active in the biotechnological area of health/medicine and respondents active in other areas of biotechnology (Sarstedt et al. 2011, p. 214). Therefore, a prerequisite for conducting multigroup comparisons is data equivalence, ensuring that "any differences found between cultures truly reflect the phenomena of interest, and are not simply a reflection of issues such as scale use tendencies and differences in construct conceptualizations" (Hult et al. 2008, p. 1028). Without having established measurement invariance, the power of statistical assessments of hypotheses is questionable and misleading conclusions might be drawn (Hult et al. 2008, p. 1028; Henseler et al. 2016, p. 409).

In the context of PLS-SEM, Henseler et al. (2016) introduced a non-parametric, three-step procedure to analyze the measurement invariance of composite models (MICOM). The procedure includes an evaluation of configural

invariance, compositional invariance, and of the equality of a construct's mean value and variance across groups (Henseler et al. 2016, p. 412ff.).

The evaluation of configural invariance involves a qualitative analysis of the constructs' specification across groups (Henseler et al. 2016, p. 413f.). Regarding the two subsamples under investigation, all of the necessary requirements are fulfilled: i.e., across groups, each measurement model is specified through the same indicators, the data treatment is identical (e.g., missing value treatment), and the PLS algorithm settings are identical. Thus, it can be concluded that configural invariance has been established.

Compositional invariance entails that the prescription for combining the indicators into constructs is the same for all groups. Therefore, compositional invariance requests that a construct's scores are created equally across groups (Henseler et al. 2016, p. 414). Henseler et al. (2016, p. 414f.) suggest conducting a (non-parametric) permutation test over the correlation c (i.e., the correlation between the constructs scores) in order to test for this type of invariance. Compositional invariance is established when a construct has a correlation in the subsamples that is not significantly lower than one (Henseler et al. 2016, p. 421).

Table 64 shows the results of 5,000 permutations. With a value of 0.970, which is very close to one, marketing proficiency has the lowest c value of all constructs in the research model. The permutation test substantiates that none of the c values are significantly different from one. It can, therefore, be concluded that compositional invariance has been established for all constructs (Henseler et al. 2016, p. 421).

Table 64: MICOM results of the model (I)

Construct	C value (=1)	95% confidence interval	Compositional invariance?
Technical fit	0.998	[0.985; 1.000]	Yes
Marketing research fit	0.999	[0.998; 1.000]	Yes
Technical proficiency	0.985	[0.947; 1.000]	Yes
Marketing proficiency	0.970	[0.958; 1.000]	Yes
R&D objective fulfillment	1.000	[1.000; 1.000]	Yes
Product competitive advantage	0.992	[0.952; 1.000]	Yes

Finally, the constructs' equality of mean values and variances is evaluated (see Table 65 and Table 66). The permutation test results (5,000 permutations) confirm that the mean value and the variance of a construct in the HHM subsample do not significantly differ from the results in the non-HHM subsample.[65] This finding holds for all constructs in the research model. Therefore, the outcomes of MICOM's final step also support measurement invariance (Henseler et al. 2016, p. 421).

[65] "Please note that MICOM builds on permutation-based confidence intervals. For this reason, the sentence on page 416 in the article by Henseler et al. (2016), "If the confidence intervals of differences in mean values and logarithms of variances between the construct scores of the first and second group include zero, the researcher can assume that the composite mean values and variances are equal.", needs to be changed. The more precise and corrected version of this sentence is as follows: "If the permutation-based confidence intervals of differences in mean values and logarithms of variances between the construct scores of the first and second group include the obtained difference, the researcher can assume that the composite mean values and variances are equal." (https://www.smartpls.com/documentation/algorithms-and-techniques/micom; last accessed August 2019).

Table 65: MICOM results of the model (II)

Construct	Difference of the construct's mean value (=0)	95% confidence interval	Equal mean values?
Technical fit	0.018	[-0.176; 0.175]	Yes
Marketing research fit	0.077	[-0.176; 0.176]	Yes
Technical proficiency	0.009	[-0.174; 0.173]	Yes
Marketing proficiency	0.022	[-0.174; 0.174]	Yes
R&D objective fulfillment	-0.124	[-0.177; 0.178]	Yes
Product competitive advantage	0.122	[-0.173; 0.179]	Yes

Table 66: MICOM results of the model (III)

Construct	Logarithm of the constructs' variance ration (=0)	95% confidence interval	Equal variances?
Technical fit	0.127	[-0.256; 0.266]	Yes
Marketing research fit	-0.017	[-0.185; 0.195]	Yes
Technical proficiency	0.159	[-0.233; 0.242]	Yes
Marketing proficiency	0.102	[-0.229; 0.252]	Yes
R&D objective fulfillment	-0.082	[-0.255; 0.270]	Yes
Product competitive advantage	0.002	[-0.307; 0.304]	Yes

In sum, all analyses of the MICOM procedure introduced by Henseler et al. (2016) support measurement invariance. Therefore, it can be concluded that full measurement invariance has been established for the two groups of data. The

results of the MICOM procedure have two implications: First, the results provide statistical evidence that it was justified to pool both subsamples (i.e., the HHM subsample and the non-HHM subsample) in the original sample of 517 cases as the basis for hypotheses testing (Henseler et al. 2016, p. 421). Second, the results fulfill the initial prerequisite for conducting comparisons of model estimation results across the two different groups of respondents (i.e., the HHM subsample and the non-HHM subsample). However, having established measurement invariance is a necessary but not sufficient precondition for multigroup PLS-SEM analyses. The evaluation of the measurement models of both subsamples remains a requirement for comparisons of models estimation results across groups (Henseler et al. 2016, p. 409; see Section 4.8.3.2.2).

4.8.3.2.2 Evaluation of the Measurement Models

The second step involves the assessment of the measurement models of both subsamples (i.e., reflective and formative measurement models; Hair et al. 2016, p. 104ff.). Three latent variables are specified as reflective measurement models (i.e., technical fit, marketing research fit, R&D objective fulfillment), and another three latent variables are specified as formative measurement models (i.e., technical proficiency, marketing proficiency, product competitive advantage).

The evaluation of reflective measurement models comprises testing for internal consistency reliability (i.e., composite reliability), convergent validity (i.e., indicator reliability, AVE), and discriminant validity (i.e., cross-loadings, Fornell-Larcker criterion, HTMT ratio) (Hair et al. 2016, p. 106).

The first criterion to be evaluated is internal consistency reliability. A measure for internal consistency reliability is composite reliability, which "determines whether the items measuring a construct are similar in their scores (i.e., if the correlations between the items are large)." (Hair et al. 2016, p. 320; see Section 4.8.1.1.1). Regarding the HHM subsample, all composite reliability values exceed the threshold value of 0.70 (Bagozzi/Yi 1988, p. 82; Hair et al. 2012b, p. 429). With values of 0.841 (technical fit), 0.921 (marketing research fit), and 0.954 (R&D objective fulfillment), all three reflective constructs have high levels of internal consistency reliability. The specific composite reliability

values in the non-HHM subsample (0.804 for technical fit, 0.919 for marketing research fit, and 0.962 for R&D objective fulfillment) are also all above the 0.70 threshold. Thus, the analysis of composite reliability suggests that internal consistency reliability has been established for both subsamples.

The second criterion to be evaluated is convergent validity. The first measure applied to test for convergent validity is indicator reliability. Indicator reliability is a measure to assess which part of an indicator's variance can be explained by its latent variable (Götz et al. 2010, p. 694; see Section 4.8.1.1.2.1). Regarding the HHM subsample, all outer loadings of the reflective constructs of marketing research fit and R&D objective fulfillment are well above the threshold value of 0.70 (Hulland 1999, p. 198). Concerning the reflective construct of technical fit, the indicators TF_1 (outer loading: 0.636) and TF_2 (outer loading: 0.687) are below the threshold. However, and in accordance with existing literature (e.g., Hulland 1999, p. 198f.; Hair et al. 2016, p. 113f.), the indicators are retained (see Section 4.8.1.1.2.1). In the non-HHM subsample, the outer loadings of the constructs of marketing research fit and R&D objective fulfillment are above the threshold value of 0.70. Again, the indicators TF_1 (outer loading: 0.652) and TF_2 (outer loading: 0.536) are below the threshold but will be retained (see Section 4.8.1.1.2.1).

The second measure applied to test for convergent validity is AVE. AVE is a measure of convergent validity to assess the degree to which a latent variable explains the variance of its indicators (Hair et al. 2016, p. 312; see Section 4.8.1.1.2.2). Concerning the HHM subsample, the AVE values of technical fit (0.574), marketing research fit (0.853), and R&D objective fulfillment (0.874) are well above the required minimum level of 0.50 (Bagozzi/Yi 1988, p. 82). The threshold value is also met for the AVE values of the reflective constructs in the non-HHM subsample (0.514 for technical fit, 0.850 for marketing research fit, and 0.895 for R&D objective fulfillment). Thus, the analyses of indicator reliability and AVE suggest that convergent validity has been established for both subsamples.

The third criterion to be evaluated is discriminant validity. The first approach used to assess the constructs' discriminant validity are cross-loadings.

Cross-loadings represent an indicator's correlation with other latent variables in the model (Hair et al. 2016, p. 315; see Section 4.8.1.1.3.1). For both subsamples, the examinations of the indicators' cross-loadings reveal that no indicator loads higher on an opposing construct (see Table 67 and Table 68). Thus, the analyses of cross-loadings suggest that discriminant validity has been established for both subsamples.

Table 67: Cross-loadings (HHM subsample)

	Technical fit	Marketing research fit	Technical proficiency	Marketing proficiency	R&D objective fulfillment	Product competitive advantage
TF_1	*0.636*	0.200	0.332	0.271	0.334	0.323
TF_2	*0.687*	0.246	0.280	0.209	0.165	0.156
TF_3	*0.887*	0.478	0.560	0.428	0.269	0.210
TF_4	*0.797*	0.468	0.435	0.323	0.169	0.075
MRF_1	0.421	*0.942*	0.482	0.516	0.235	0.219
MRF_2	0.472	*0.905*	0.424	0.429	0.120	0.108
OF_1	0.274	0.134	0.401	0.337	*0.934*	0.387
OF_2	0.282	0.212	0.429	0.372	*0.947*	0.462
OF_3	0.322	0.207	0.392	0.333	*0.924*	0.439

Table 68: Cross-loadings (non-HHM subsample)

	Technical fit	Marketing research fit	Technical proficiency	Marketing proficiency	R&D objective fulfillment	Product competitive advantage
TF_1	*0.652*	0.196	0.423	0.379	0.357	0.390
TF_2	*0.536*	-0.003	0.208	0.210	0.146	0.087
TF_3	*0.851*	0.341	0.506	0.524	0.262	0.341
TF_4	*0.786*	0.340	0.443	0.458	0.213	0.152
MRF_1	0.358	*0.953*	0.479	0.546	0.184	0.293
MRF_2	0.270	*0.890*	0.328	0.398	0.068	0.119
OF_1	0.335	0.110	0.522	0.402	*0.957*	0.509
OF_2	0.331	0.163	0.507	0.413	*0.956*	0.509
OF_3	0.337	0.148	0.492	0.394	*0.925*	0.437

The second approach used to assess the constructs' discriminant validity is the Fornell-Larcker criterion. The Fornell-Larcker criterion (Fornell/Larcker 1981, p. 46) demands that the square root of the AVE of each latent variable is higher than the latent variable's highest correlation with any other construct in the structural model (Hair et al. 2016, p. 129; see Section 4.8.1.1.3.2). The analyses of both subsamples indicate that the constructs exhibit discriminant validity (see Table 69 and Table 70).

Table 69: Fornell-Larcker criterion (HHM subsample)

	1	2	3	4	5	6	7	8	9
1 Technical fit	*0.758*								
2 Marketing research fit	0.479	*0.924*							
3 Technical proficiency	0.553	0.493							
4 Marketing proficiency	0.424	0.516	0.711						
5 R&D objective fulfillment	0.313	0.199	0.436	0.372	*0.935*				
6 Product competitive advantage	0.252	0.184	0.442	0.480	0.461				
7 Number project partners	-0.040	-0.111	-0.074	-0.045	-0.065	-0.036	1.000		
8 Project duration	-0.013	-0.032	0.011	0.038	-0.026	0.124	0.371	1.000	
9 Size project team	0.075	0.067	0.034	0.109	0.039	0.039	0.488	0.440	1.000

Note: Table shows the results of the Fornell-Larcker criterion assessment with the square root of the reflective constructs' AVE on the diagonal (in italics) and the correlations between the constructs in the off-diagonal position.

Table 70: Fornell-Larcker criterion (non-HHM subsample)

	1	2	3	4	5	6	7	8	9
1 Technical fit	*0.717*								
2 Marketing research fit	0.348	*0.922*							
3 Technical proficiency	0.580	0.451							
4 Marketing proficiency	0.577	0.525	0.716						
5 R&D objective fulfillment	0.353	0.148	0.536	0.426	*0.946*				
6 Product competitive advantage	0.369	0.241	0.510	0.485	0.514				
7 Number project partners	-0.088	-0.004	-0.059	-0.003	-0.111	-0.110	1.000		
8 Project duration	0.026	0.078	0.120	0.018	-0.058	-0.047	0.292	1.000	
9 Size project team	0.009	0.104	0.093	0.111	-0.074	-0.092	0.470	0.380	1.000

Note: Table shows the results of the Fornell-Larcker criterion assessment with the square root of the reflective constructs' AVE on the diagonal (in italics) and the correlations between the constructs in the off-diagonal position.

The third approach used to assess the constructs' discriminant validity is the HTMT ratio (Henseler et al. 2015, p. 115f.; Hair et al. 2016, p. 118; see Section 4.8.1.1.3.3). For both subsamples, the HTMT ratio values are presented in Table 71 and Table 72, respectively. As can be seen, the HTMT ratio values are all clearly under the threshold value of 0.90. In addition, all HTMT values are

significantly different from 1.[66] Thus, the analysis of the HTMT ratio suggests that discriminant validity has been established.

Table 71: HTMT ratio (HHM subsample)

	1	2	5	7	8	9
1 Technical fit						
2 Marketing research fit	0.588					
5 R&D objective fulfillment	0.370	0.216				
7 Number project partners	0.079	0.128	0.065			
8 Project duration	0.042	0.037	0.028	0.371		
9 Size project team	0.092	0.073	0.040	0.488	0.440	

[66] The level of significance was tested by using the bootstrapping procedure. As recommended by Hair, Sarstedt, Ringle, & Mena (2012, p. 429) and Hair et al. (2016, p. 160), the following options were selected using the bootstrapping procedure in SmartPLS 3 (Ringle et al. 2015): the selected number of bootstrap samples was 5000 (subsamples); the no sign change option was chosen to obtain the most conservative results (sign change option); the number of bootstrap cases equalled the number of valid observations.

Table 72: HTMT ratio (non-HHM subsample)

	1	2	5	7	8	9
1 Technical fit						
2 Marketing research fit	0.433					
5 R&D objective fulfillment	0.423	0.155				
7 Number project partners	0.116	0.034	0.116			
8 Project duration	0.036	0.097	0.061	0.292		
9 Size project team	0.065	0.120	0.078	0.470	0.380	

A summary of the results is presented in Table 73 and Table 74. Overall, these results provide clear support for the measures' reliability, as well as the measures' convergent and discriminant validity. To conclude, the assessment provides evidence that the measurement quality of the reflective measured latent variables (i.e., technical fit, marketing research fit, and R&D objective fulfillment) complies with the requirements of PLS-SEM for both subsamples.

Table 73: Reflective measurement models evaluation (HHM subsample)

Latent Variable	Indicator	Convergent Validity		Internal Consistency Reliability	Discriminant Validity		
		Indicator Reliability	AVE	Composite Reliability	Cross-Loading	Fornell–Larcker Criterion	HTMT
		>0.70	>0.50	>0.70	Outer loadings higher than all its cross-loadings?	Square root of each construct's AVE greater than its highest correlation with any other construct?	HTMT below 0.90?
Technical fit	TF_1	0.636	0.574	0.841	Yes	Yes	Yes
	TF_2	0.687					
	TF_3	0.887					
	TF_4	0.797					
Marketing research fit	MRF_1	0.942	0.853	0.921	Yes	Yes	Yes
	MRF_2	0.905					
R&D objective fulfillment	OF_1	0.934	0.874	0.954	Yes	Yes	Yes
	OF_2	0.947					
	OF_3	0.924					

Table 74: Reflective measurement models evaluation (non-HHM subsample)

Latent Variable	Indicator	Convergent Validity		Internal Consistency Reliability	Discriminant Validity		
		Indicator Reliability	AVE	Composite Reliability	Cross-Loading	Fornell–Larcker Criterion	HTMT
		>0.70	>0.50	>0.70	Outer loadings higher than all its cross-loadings?	Square root of each construct's AVE greater than its highest correlation with any other construct?	HTMT below 0.90?
Technical fit	TF_1	0.652	0.514	0.804	Yes	Yes	Yes
	TF_2	0.536					
	TF_3	0.851					
	TF_4	0.786					
Marketing research fit	MRF_1	0.953	0.850	0.919	Yes	Yes	Yes
	MRF_2	0.890					
R&D objective fulfillment	OF_1	0.957	0.895	0.962	Yes	Yes	Yes
	OF_2	0.956					
	OF_3	0.925					

The evaluation of formative measurement models encompasses the assessment of collinearity of the indicators, as well as the assessment of indicator weights and the significance of weights (Hair et al. 2016, p. 137ff.).

The approach used to assess collinearity of formative indicators is the VIF (Midi et al. 2010, p. 259; see Section 4.8.1.2.1). Each indicator's VIF value should be less than 5.0 to avoid collinearity issues (Hair et al. 2011, p. 145). For both subsamples, all VIF values are uniformly below the threshold value of 5. Thus, the results provide evidence that no collinearity issues arise in the formative measurement models for both subsamples.

The indicators' relative contribution to the constructs is measured through indicator weights and the significance of these weights (Hair et al. 2016, p. 145f.). Each indicator represents a substantial part of the construct's domain (see Section 4.8.1.2.2). The question to be investigated is whether formative indicators truly (i.e., if the outer weights significantly differ from zero) contribute to causing the latent variable (Hair et al. 2016, p. 146).[67] For the HHM subsample, all formative indicators are significant at a 5% level, except TP_2, TP_3, TP_4, MP_1, and MP_3. However, the indicators are retained and interpreted as absolutely important, since their outer loadings are above the threshold value of 0.50 (Hair et al. 2016, p. 148). For the non-HHM subsample, all formative indicators are significant at a 5% level, except TP_4, TP_5, MP_2, MP_3, and MP_6. Again, the indicators are retained and interpreted as absolutely important, since their outer loadings are above the threshold value of 0.50 (Hair et al. 2016, p. 148).

Overall, the evaluation of the formative measurement models suggests that no collinearity issues arise and each formative indicator contributes to its related latent variable. For both subsamples, the assessment provides evidence that the measurement quality of the formative measured latent variables (i.e., technical proficiency, marketing proficiency, and product competitive advantage) complies with the requirements of PLS-SEM. The results are summarized in Table 75 and Table 76, respectively.

[67] Tests of significance were conducted using the bootstrapping procedure (5,000 replications).

Table 75: Formative measurement models evaluation (HHM subsample)

Formative Construct	Formative Indicator	VIF Value	Outer Weight (Outer Loading)	t-Value
Technical proficiency	TP_1	1.651	0.321 (0.787)	3.834***
	TP_2	2.136	0.179 (0.769)	1.944
	TP_3	1.919	0.102 (0.623)	1.094
	TP_4	2.142	0.124 (0.702)	1.368
	TP_5	2.436	0.222 (0.822)	1.962*
	TP_6	2.312	0.330 (0.837)	3.546***
Marketing proficiency	MP_1	1.997	0.031 (0.637)	0.386
	MP_2	1.954	0.310 (0.704)	3.713***
	MP_3	2.232	0.090 (0.762)	1.044
	MP_4	2.342	0.242 (0.802)	2.473**
	MP_5	2.262	0.300 (0.827)	3.939***
	MP_6	2.039	0.299 (0.838)	3.720***
Product competitive advantage	LV_PM	2.635	0.422 (0.921)	2.347**
	LV_PS	2.635	0.634 (0.966)	3.692***

Note: *Significant for $p < .05$. (t-value 1.96) **Significant for $p < .01$. (t-value 2.58) ***Significant for $p < .001$. (t-value 3.29)

Table 76: Formative measurement models evaluation (non-HHM subsample)

Formative Construct	Formative Indicator	VIF Value	Outer Weight (Outer Loading)	t-Value
Technical proficiency	TP_1	1.557	0.221 (0.693)	2.504**
	TP_2	1.760	0.316 (0.793)	3.254**
	TP_3	1.714	0.198 (0.690)	2.280*
	TP_4	1.908	0.138 (0.681)	1.149
	TP_5	1.981	0.093 (0.697)	0.990
	TP_6	1.934	0.371 (0.812)	4.281***
Marketing proficiency	MP_1	2.488	0.370 (0.843)	3.564***
	MP_2	2.354	0.129 (0.742)	1.342
	MP_3	2.167	0.108 (0.725)	1.262
	MP_4	1.897	0.217 (0.704)	2.511*
	MP_5	1.958	0.283 (0.802)	2.965**
	MP_6	1.873	0.177 (0.756)	1.868
Product competitive advantage	LV_PM	2.052	0.610 (0.945)	3.642***
	LV_PS	2.052	0.468 (0.905)	2.639**

Note: *Significant for $p < .05$. (t-value 1.96) **Significant for $p < .01$. (t-value 2.58) ***Significant for $p < .001$. (t-value 3.29)

4.8.3.2.3 Multigroup Analysis

After the successful evaluation of measurement invariance and the measurement models, the multigroup analysis procedure in PLS path modeling is conducted (Sarstedt et al. 2011). Before comparing the path coefficients of the two subsamples, it is advised to test for collinearity issues in order to ensure the quality of the prediction (see Section 4.8.2.1). As depicted in Table 77 and Table 78, all VIF values are clearly below the threshold value of 0.50 (Sarstedt et al. 2011, p. 145; Hair et al. 2016, p. 209). Hence, the results demonstrate that collinearity is not an issue in the structural path model for both subsamples.

Table 77: Collinearity assessment (HHM subsample)

	1	2	3	4	5	6
1 Technical fit			1.226	1.302		1.594
2 Marketing research fit				1.326		1.583
3 Technical proficiency					1.012	2.556
4 Marketing proficiency			1.238			2.238
5 R&D objective fulfillment						1.272
6 Product competitive advantage						

Table 78: Collinearity assessment (non-HHM subsample)

	1	2	3	4	5	6
1 Technical fit			1.524	1.149		1.660
2 Marketing research fit				1.153		1.443
3 Technical proficiency					1.035	2.722
4 Marketing proficiency			1.530			2.556
5 R&D objective fulfillment						1.490
6 Product competitive advantage						

Table 79 shows the results of the structural model evaluation for both subsamples. The bootstrap procedure using 5,000 samples and a number of cases equal to the specific subsample sizes (using the individual sign change option) was applied. Path estimation indicates that technical fit has no direct effect on product competitive advantage (HHM subsample: $\beta = 0.003$, n.s.[68]; non-HHM subsample: $\beta = 0.029$, n.s.), rejecting hypothesis 1 for both subsamples. Likewise, marketing research fit does not enhance product competitive advantage (HHM subsample: $\beta = -0.103$, n.s.; non-HHM subsample: $\beta = -0.001$, n.s.), rejecting hypothesis 2 for both subsamples. Confirming hypothesis 3 for both subsamples, technical fit positively affects technical proficiency (HHM subsample: $\beta = 0.309$, $p < 0.001$; non-HHM subsample: $\beta = 0.239$, $p < 0.001$). Technical fit also

[68] n.s. = not significant.

increases marketing proficiency (HHM subsample: $\beta = 0.227$, $p < 0.001$; non-HHM subsample: $\beta = 0.453$, $p < 0.001$), supporting hypothesis 4 for both subsamples. Furthermore, marketing research fit enhances marketing proficiency (HHM subsample: $\beta = 0.400$, $p < 0.001$; non-HHM subsample: $\beta = 0.363$, $p < 0.001$), supporting hypothesis 5 for both subsamples. Confirming hypothesis 6 for both subsamples, marketing proficiency directly affects technical proficiency (HHM subsample: $\beta = 0.584$, $p < 0.001$; non-HHM subsample: $\beta = 0.574$, $p < 0.001$). Supporting hypothesis 7 for both subsamples, marketing proficiency positively affects product competitive advantage (HHM subsample: $\beta = 0.333$, $p < 0.001$; non-HHM subsample: $\beta = 0.219$, $p < 0.05$). Technical proficiency has no direct effect on product competitive advantage (HHM subsample: $\beta = 0.118$, n.s.; non-HHM subsample: $\beta = 0.185$, n.s.), rejecting hypothesis 8 for both subsamples. Confirming hypothesis 9 for both subsamples, technical proficiency directly affects R&D objective fulfillment (HHM subsample: $\beta = 0.431$, $p < 0.001$; non-HHM subsample: $\beta = 0.554$, $p < 0.001$). Supporting the last hypothesis 10 for both subsamples, R&D objective fulfillment enhances product competitive advantage (HHM subsample: $\beta = 0.310$, $p < 0.001$; non-HHM subsample: $\beta = 0.301$, $p < 0.001$).

The presented path estimations demonstrate that both subsamples comply with the results of the path analysis conducted using the complete data set of 517 cases at least for a significance level of $p < 0.05$ (i.e., all hypotheses are significant, except for H1, H2, and H8; see Section 4.8.2.2). The next question that emerges in the context of multigroup analysis is whether numeric differences between subsample specific path coefficients are statistically significant (Sarstedt et al. 2011, p. 210).

Table 79: Standardized path coefficients and significances for the subsamples

Path Relationship	Path Coefficient (t-Value) HHM Subsample	Non-HHM Subsample
Technical fit → Product competitive advantage	0.003 (0.040)	0.029 (0.290)
Marketing research fit → Product competitive advantage	-0.103 (1.526)	-0.001 (0.010)
Technical fit → Technical proficiency	0.309 (5.998)***	0.239 (3.982)***
Technical fit → Marketing proficiency	0.227 (3.487)***	0.453 (7.854)***
Marketing research fit → Marketing proficiency	0.400 (6.151)***	0.363 (6.025)***
Marketing proficiency → Technical proficiency	0.584 (12.345)***	0.574 (9.626)***
Marketing proficiency → Product competitive advantage	0.333 (4.107)***	0.219 (1.970)*
Technical proficiency → Product competitive advantage	0.118 (1.233)	0.185 (1.803)
Technical proficiency → R&D objective fulfillment	0.431 (7.414)***	0.554 (9.536)***
R&D objective fulfillment → Product competitive advantage	0.310 (4.441)***	0.301 (4.052)***

Notes: β = standardized path coefficient; *Significant for $p < 0.05$ (t-value 1.96); **Significant for $p < .01$ (t-value 2.58); ***Significant for $p < .001$ (t-value 3.29).

In correspondence with the nonparametric nature of PLS-SEM, Sarstedt et al. (2011, p. 195) and Hair et al. (2016, p. 294f.) propose two multigroup analysis approaches that do not rely on distributional assumptions: the permutation test (Dibbern/Chin 2005; Chin/Dibbern 2010) and the PLS-MGA approach by Henseler et al. (2009). However, the former is limited in that this approach requires the group-specific sample sizes to be similar (Sarstedt et al. 2011, p. 201), which does not apply to the two subsamples under investigation. Therefore, the PLS-MGA approach (Henseler et al. 2009), which does not inherit such a limitation (Sarstedt et al. 2011, p. 202f.), is chosen in order to conduct the multigroup analysis.

The PLS-MGA approach relies on the bootstrapping procedure and compares each estimate of group one with all other estimates of the same parameter in group two (Henseler et al. 2009, p. 307; Sarstedt et al. 2011, p. 202; Hair et al. 2016, p. 294). "By counting the number of occurrences where the bootstrap estimate of the first group is larger than those of the second group, the approach derives a probability value for a one-tailed test" (Hair et al. 2016, p. 294).

Table 80 provides the results of the multigroup comparisons based on Henseler's (2009) PLS-MGA approach (5,000 replications). The analysis shows that there are no significant differences between the path coefficients of the two subsamples.

Table 80: Multigroup comparison test results

Path Relationship	|diff|	$p_{Henseler}$
Technical fit → Product competitive advantage	0.026	0.581
Marketing research fit → Product competitive advantage	0.103	0.854
Technical fit → Technical proficiency	0.070	0.189
Technical fit → Marketing proficiency	0.226	0.995
Marketing research fit → Marketing proficiency	0.037	0.336
Marketing proficiency → Technical proficiency	0.010	0.447
Marketing proficiency → Product competitive advantage	0.114	0.204
Technical proficiency → Product competitive advantage	0.067	0.683
Technical proficiency → R&D objective fulfillment	0.123	0.932
R&D objective fulfillment → Product competitive advantage	0.009	0.466

In sum, it is shown that there is no data heterogeneity regarding the two groups (i.e., the HHM subsample and the non-HHM subsample), which would have threatened the validity of the PLS-SEM results and led to misleading

conclusions (Sarstedt et al. 2009, p. 185ff.; Sarstedt et al. 2011, p. 197; Hair et al. 2016, p. 290). The MICOM analysis (Henseler et al. 2016) provided evidence that it was justified with regard to measurement invariance to pool both subsamples in the overall sample of 517 cases as the basis for hypotheses testing (Henseler et al. 2016, p. 421). Then, the PLS-MGA approach (Henseler et al. 2009) also demonstrated that the relationships (i.e., path coefficients and their significances) in the research model of this thesis do not differ between the biotechnological area of human health/medicine and other biotechnological areas of activity.

4.8.4 Summary of the Results of the Empirical Analysis of the Research Model

This section summarizes the main findings of the empirical investigation of the research model. The initial evaluation of the measurement models demonstrated that the reflective measures (i.e., technical fit, marketing research fit, and R&D objective fulfillment) are reliable and valid, the formative measures are not subjects to collinearity issues and each formative indicator contributes to its related latent variable. Therefore, all requirements for conducting a PLS-SEM analysis were fully satisfied.

The evaluation of the structural model involved various procedures for hypotheses testing. The resulting conclusions regarding this assessment are now briefly summarized:

Rejecting hypothesis H1, technical fit has no direct effect on product competitive advantage ($\beta = 0.001$, n.s.). However, analyzing total effects indicates that technical fit ultimately (i.e., via mediating constructs) has an impact on product competitive advantage (0.224, $p < 0.001$). Subsequent mediation analyses illuminated the indicated association between technical fit and product competitive advantage. Mediation analysis showed that technical proficiency does not directly mediate the effect of technical fit on product competitive advantage, since technical proficiency is associated with product competitive advantage only through the mediating construct of R&D objective fulfillment (this will be discussed later in this section). Nevertheless, mediation analysis demonstrated that marketing proficiency represents a mechanism that underlies the relationship

between technical fit and product competitive advantage. High levels of technical fit lead to high levels of marketing proficiency and high levels of marketing proficiency lead to product competitive advantage. Thus, an R&D project's fit with the available skills and resources does not automatically lead to competitive advantages (Day/Wensley 1988, p. 7).

Rejecting hypothesis H2, marketing research fit does not enhance product competitive advantage (β = -0.052, n.s.). Analyzing total effects indicates that marketing research fit ultimately (i.e., via mediating constructs) has an impact on product competitive advantage (0.116, $p < 0.05$). Mediation analysis showed that marketing proficiency fully mediates the relationship between marketing research fit and product competitive advantage. High levels of marketing research fit lead to high levels of marketing proficiency, and high levels of marketing proficiency lead to product competitive advantage. Thus, it is once again shown that an R&D project's fit with the available skills and resources does not automatically lead to competitive advantages (Day/Wensley 1988, p. 7).

Confirming hypothesis H3, technical fit positively affects technical proficiency ($\beta = 0.279$, $p < 0.001$). In particular, technical fit exhibits a small to almost medium effect size (f^2) of 0.138 (i.e., its relative impact; Hair et al. 2016, p. 317) on technical proficiency. Technical fit also increases marketing proficiency, supporting hypothesis H4 ($\beta = 0.321$, $p < 0.001$). In this relationship, technical fit has a small to almost medium effect size (f^2) of 0.131(i.e., its relative impact; Hair et al. 2016, p. 317) on marketing proficiency. Furthermore, marketing research fit enhances marketing proficiency, supporting hypothesis H5 ($\beta = 0.371$, $p < 0.001$). Specifically, marketing research fit has a medium effect size (f^2) of 0.174 (i.e., its relative impact; Hair et al. 2016, p. 317) on marketing proficiency. In correspondence with information-processing theory (e.g., Tushman/Nadler 1978; Daft/Lengel 1986; Sinkula 1994; Song et al. 2005), the results demonstrate that the abilities to gather, interpret, and utilize technical and marketing information need to match the information-processing requirements of an R&D project in order to proficiently conduct the various technical and marketing activities (Tushman/Nadler 1978).

Confirming hypothesis H6, marketing proficiency directly affects technical proficiency ($\beta = 0.578$, $p < 0.001$). In this association, marketing proficiency has a large effect size (f^2) of 0.589 (i.e., its relative impact; Hair et al. 2016, p. 317) on technical proficiency. An additional mediation analysis revealed that marketing proficiency partially mediates the relationship between technical fit and technical proficiency. Higher levels of technical fit increase technical proficiency directly but also increase marketing proficiency, which in turn leads to higher levels of technical proficiency. Hence, some extent of the effect of technical fit on technical proficiency is explained by marketing proficiency. The mediating feature of marketing proficiency illustrates the importance of marketing-related activities, which provide data that are transformed into information that guide the direction of the development process and foster the proficient execution of technical activities.

Supporting hypothesis H7, marketing proficiency positively affects product competitive advantage ($\beta = 0.293$, $p < 0.001$). However, marketing proficiency exhibits only a small effect size (f^2) of 0.058 (i.e., its relative impact; Hair et al. 2016, p. 317) on product competitive advantage. Nonetheless, marketing proficiency has the strongest total effect on product competitive advantage (0.454, $p < 0.001$) of all predictor variables in the research model. The rationale of these findings (i.e., small relative impact of marketing proficiency on product competitive advantage while simultaneously exhibiting the strongest total effect on the target construct) is that marketing proficiency is positively associated with technical proficiency, which in turn has an impact on product competitive advantage via the mediating construct of R&D objective fulfillment (this will be discussed later in this section). The proficient execution of marketing-related activities generates information that can be integrated into the development process by matching product attributes and functionalities with the needs of end users and in compliance with competitive offerings. These predevelopment activities provide the basis for proficiently executing the actual development activities (i.e., technical activities), and represent the efforts that enable a cooperative R&D project to position the new product as superior to competing offerings within a given market and as meaningful to potential users.

Rejecting hypothesis H8, technical proficiency has no direct effect on product competitive advantage ($\beta = 0.131$, n.s.). However, technical proficiency has the second strongest total effect on product competitive advantage (0.278, $p < 0.001$) through its association with R&D objective fulfillment. Regarding this association and confirming hypothesis H9, technical proficiency directly affects R&D objective fulfillment ($\beta = 0.477$, $p < 0.001$). Moreover, technical proficiency has a medium effect size (f^2) of 0.290 (i.e., its relative impact; Hair et al. 2016, p. 317) on R&D objective fulfillment. Supporting the final hypothesis H10, R&D objective fulfillment enhances product competitive advantage ($\beta = 0.307$, $p < 0.001$) while exhibiting a small effect size (f^2) of 0.108 on the target construct. A corresponding mediation analysis showed that R&D objective fulfillment fully mediates the relationship between technical proficiency and product competitive advantage. High levels of technical proficiency lead to high levels of R&D objective fulfillment, and high levels of R&D objective fulfillment lead to product competitive advantage. Thus, the proficient execution of technical activities creates valuable data and information for the iterative process of R&D, which assist in the fulfillment of the initial R&D objectives. Having defined the objectives of the research venture based on user preferences, market trends and "appeal" characteristics that differentiate the product, the fulfillment of the R&D objective leads to the achievement of a product competitive advantage.

5 Summary, Conclusion, and Outlook

The concluding section of this thesis involves an overview of its findings, theoretical contributions and implications, practical implications, as well as limitations and avenues for future research. The first section 5.1 begins with an overall summary of this thesis. The second section 5.2 addresses the contributions and implications for theory. The third section 5.3 presents practical implications with respect to the drivers for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. The fourth section 5.4 discusses the limitations of the investigation along with further research needs.

5.1 Overall Summary

The overall objective of this thesis was to identify and empirically test the determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. In particular, subject of this thesis was the following three research objectives:

- Research objective 1: The elaboration of the theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI.
- Research objective 2: The identification and evaluation of determining factors for achieving a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI.
- Research objective 3: To show how cooperative R&D projects between biotechnology firms and PRI should be designed and executed to support the achievement of a product competitive advantage.

The motivation of the current thesis was the conclusion that though extant literature contributes to the understanding of the influence of cooperative R&D project characteristics and factors related to knowledge transfer on different measures of success, there had been no investigation of cooperative R&D project success between firms and PRI from a product competitive advantage perspective. There was a significant research gap related to the achievement of a product

competitive advantage in cooperative R&D projects between firms and PRI and the need for an empirical investigation with regard to the respective determinants of success and their interrelationships.

The investigation of the determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective was divided into four procedural steps, which successively pursued the objectives of this thesis:

In the first step, conceptual principles were discussed as a prerequisite for developing a model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective. The close association of superior and meaningful products with successful NPD ventures (Cooper 1979b; Cooper/Kleinschmidt 1987; Zirger/Maidique 1990; Cooper/Kleinschmidt 1993; Song/Parry 1996; Song/Parry 1997b; Li/Calantone 1998; Song/Parry 1999; McNally et al. 2010; Langerak et al. 2004; Nakata et al. 2006; Veldhuizen et al. 2006) as well as the role of project-related variables (i.e., fit of available resources and skills with the project requirements) and process-related factors (i.e., the proficient execution of NPD activities) for achieving a product competitive advantage were presented (Song/Parry 1996; Song/Parry 1997b; Nakata et al. 2006; Harmancioglu et al. 2009). Subsequently, the characteristics of the biotechnology industry were described (e.g., Schüler 2016), and state-of-the-art-research on R&D cooperations in biotechnology reviewed (e.g., Rothaermel/Deeds 2004; Ortiz 2013).

The second step involved the development of the research model and the formulation of the hypotheses of the thesis. In particular, the underlying theoretical foundations that explain the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI were elaborated. These theoretical foundations involved resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978). According to resource-based theory, competitive advantages are hypothesized to be the consequence of resources and skills a cooperative R&D project possesses. Information-processing theory suggests that a fit of possessed resources and skills with the R&D project’s needs enables the

proficient execution of R&D activities, which fosters the development of a superior and meaningful product (i.e., product competitive advantage). Based on the theoretical framework, the research model of determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective was presented. In this regard, the hypotheses of the thesis were discussed. In total, ten cause-effect relationships were proposed.

The empirical analysis of the research model was in the center of the third step. Cooperative R&D projects between biotechnology firms and PRI were determined as the object of study. These cooperative R&D ventures were defined as formal collaborative arrangements between at least one biotechnology firm and at least one PRI with the objective to cooperate on R&D activities (Petruzzelli 2011, p. 310). SEM (Chin 1998b) was chosen for the empirical evaluation of the research model, since this approach allowed to capture the interrelationships among determinants as well as to assess in which ways factors contribute to achieving a product competitive advantage (Hair et al. 2016). Data collection was accomplished by means of an online survey. Therefore, the variables of the research model were operationalized on the basis of existing NPD literature and the corresponding items were summarized in a questionnaire. A total of 517 questionnaires were included in the empirical analysis. The data were analyzed using variance-based SEM (i.e., PLS-SEM) in order to conduct hypotheses testing. This evaluation of the empirical data included an additional mediation analysis and the comparison of effects in subsamples (i.e., a multigroup analysis to compare the hypothesized paths in the research model and to detect potential differences across data groups).

The fourth and final step is part of this concluding section, that is, an overall summary of the thesis, the discussion with regard to theoretical contributions and implications, practical implications, as well as illustrating limitations of the present study in combination with avenues for future research.

5.2 Theoretical Contributions and Implications

This section highlights the theoretical contributions and implications of this thesis. Corley/Gioia (2011, p. 12) categorize theoretical contributions into two dimensions, originality and utility.

Originality in the context of theoretical contributions refers to theoretical insights that advance the understanding of management and organizations (Corley/Gioia 2011, p. 16) by "offering a critical redirection of existing views or by offering an entirely new point of view on phenomena" (Conlon 2002, p. 489). Though existing literature greatly contributed to the understanding of the influence of cooperative R&D project characteristics and factors related to knowledge transfer on different measures of success (e.g., Mora-Valentin et al. 2004; Petruzzelli 2011; Schwartz et al. 2012), cooperative R&D project success between firms and PRI had not been investigated before from a product competitive advantage perspective. However, the importance of such an investigation is inherent in the underlying motivation that leads to the formation of cooperative R&D projects between biotechnology firms and PRI (i.e., R&D project success in the form of a meaningful and superior biotechnological product).

In general, cooperative R&D projects between firms and PRI are initiated with the goal of achieving specific objectives and success of such ventures is determined by the achievement of the pursued objectives (Mora-Valentin et al. 2004, p. 18). In cooperative R&D projects between biotechnology firms and PRI, the objective or anticipated outcome is a product (i.e., a biotechnological invention; Rothaermel/Deeds 2004, p. 204) which is meaningful to users and superior to competitive offerings (i.e., product competitive advantage) (Ernst & Young 2013, p. 31; Ernst & Young 2014, p. 11). Thus, the appraisal of product competitive advantage is essential in order to know to what degree the initially defined objective in cooperative R&D projects between biotechnology firms and PRI have been met. Under the premise that projects must be planned and executed with its objectives in mind (Shenhar et al. 2001, p. 713f.), it is of special interest in the context of success of cooperative R&D projects between biotechnology firms and PRI which project-related and process-related factors are beneficial for

obtaining a product competitive advantage. By addressing this research need, the presented thesis not only extends the current understanding of cooperative R&D projects between (biotechnology) firms and PRI but offers completely new points of view by applying the novel perspective of product competitive advantage on the phenomenon of success of such cooperative R&D ventures.

Regarding utility in the context of theoretical contributions, the insight of a study must be useful as well (Corley/Gioia 2011, p. 17f.). It must have the potential to "improve the current research practice of informed scholars" (Whetten 1990, p. 581). "In a very practical sense, good theory helps identify what factors should be studied and how and why they are related" (Hitt/Smith 2005, p. 2). In order to identify the predictors of product competitive advantage in cooperative R&D projects between biotechnology firms and PRI, this thesis drew from the theoretical foundations of resource-based theory (e.g., Barney 1991; Peteraf 1993) and information-processing theory (e.g., Tushman/Nadler 1978).

The resource-based theory represents a theoretical approach that aims to explain how competitive advantages of organizations can be realized. Essentially, it is suggested that an organization can be conceptualized as an assembly or set of resources and capabilities characterized by a certain degree of heterogeneity (Eisenhardt/Martin 2000, p. 1105). For a resource or capability to be regarded as a potential driver of competitive advantages, it is supposed to support the organization in its efforts to create greater value, as well as be rare among the competition, imperfectly imitable and difficult to substitute (Peteraf/Barney 2003, p. 316). Such critical resources are assumed to leverage an organization's ability to produce more economically and/or better satisfy end user (e.g., customer) needs (Barney 1991, p. 101; Peteraf/Barney 2003, p. 311ff.).

In correspondence with the assumptions of resource-based theory, it was hypothesized in the research model that a fit between an R&D project's needs and the partners' combined resources and skills (i.e., technical fit and marketing research fit) has a positive direct impact on product competitive advantage. Such positive relationships were expected in the research model, since the principal criteria for selecting a partner in the biotechnology industry are scientific excellence, professional expertise as well as technical and human capacities in a

specific field of research (Ortiz 2013, p. 231ff.). The criterion of scarce resources is reflected in the tacit knowledge and expertise of researchers from PRI and biotechnology firms, which are difficult to imitate and to substitute (Coff 1997, p. 374).

However, the empirical analysis of the research model did not confirm the hypothesized relationship between the fit of resources and skills and product competitive advantage. In particular, neither technical fit nor marketing research fit has a positive direct effect on product competitive advantage in the context of cooperative R&D projects between biotechnology firms and PRI. In contrast to the notion of resource-based theory, these results do not indicate that resources and capabilities have a share in obtaining a product competitive advantage. Nevertheless, analyzing total effects (i.e., the sum of direct and indirect effects) demonstrated that technical fit and marketing research fit ultimately have an influence on product competitive advantage. The interpretation of direct effects is explicitly recommended by Hair et al. (2016, p. 197f.) for studies aiming to explore the differential influence of several driver variables on a target variable through one or more mediating variables. Therefore, the evaluation of the total effects provides support for the positive relationship between the fit of resources and capabilities with the R&D ventures needs and product competitive advantage. An additional mediation analysis also confirmed that the association between marketing research fit, as well as technical fit, and product competitive advantage is mediated by marketing proficiency. Therefore, the results provide support for the notion of resource-based theory that competitive advantages derive from resources and capabilities which are "scarce (rare) and superior in use, relative to others" (Peteraf/Barney 2003, p. 311). A cooperative R&D project's fit with the available resources and capabilities raises its efficiency in the sense that they (i.e., resources and capabilities) enable an R&D venture to conduct the tasks of R&D more proficiently and eventually foster the development of a superior and meaningful biotechnological product (i.e., product competitive advantage).

Information-processing theory casts light on the relationship between a cooperative R&D project's fit with the available resources and skills and product competitive advantage. As argued by Day/Wensley (1988, p. 311), the results

demonstrated that superior resources and skills are not automatically transferred into competitive advantages.

Information-processing theory (Galbraith 1974) focuses on the relationships between information and the execution of activities and explains how the quality of activities can be improved through the processing and use of information (Schultz 2006, p. 40). From an information-processing view, cooperative R&D projects can be regarded as interpretation systems which scan and collect data (i.e., the process of monitoring the environment and providing environmental data), interpret that data (i.e., giving meaning to the data), and finally, learn by drawing conclusions upon the interpretation (Daft/Weick 1984; Keller 1994, p. 168).

In the particular process of cooperative R&D projects, activities such as market research, business analysis, prototype development and trials produce data, which need to be converted into information (i.e., "data endowed with relevance and purpose"; Drucker 1988, p. 46). The conversion of data from a specific domain (e.g., knowledge of a specific scientific domain) into information requires knowledge of that specific subject domain (Drucker 1988, p. 46; Gray 2000, p. 179). The greater the knowledge an individual has of a subject domain, the better he or she will be able to grasp meaning inherent in data drawn from that domain (Cohen/Levinthal 1990, p. 128; Gray 2000, p. 179). The ability of cooperative R&D project members (either individually or collectively) to gather and interpret data, as well as utilizing the resulting information for the purpose of R&D is represented in the venture's information-processing capability (Egelhoff 1991, p. 346). From a theoretical perspective, the information-processing capability has to fit the information-processing requirements facing a cooperative R&D project in order to be effective (Tushman/Nadler 1978).

In correspondence with the assumptions of information-processing theory, it was hypothesized in the research model that a fit between an R&D project's needs and the partners' combined resources and skills (i.e., technical fit and marketing research fit) has a positive direct impact on the proficient execution of the various R&D activities that characterize cooperative R&D projects between biotechnology firms and PRI. Confirming the hypothesized relationships,

technical fit positively affects the proficient execution of technical and marketing-related activities. Furthermore, marketing research fit enhances the competent execution of marketing-related activities. Thus, the results of the empirical investigation showed that the abilities to gather, interpret, and utilize technical and marketing information need to match the information-processing requirements of an R&D project in order to proficiently conduct the various technical and marketing activities (Tushman/Nadler 1978).

Moreover, this thesis highlights the importance of marketing-related activities in cooperative R&D projects between biotechnology firms and PRI. Overall, the competent execution of marketing-related activities has the strongest total effect on product competitive advantage of all predictor variables in the research model. The proficient execution of marketing-related activities generates information that can be integrated into the development process by matching product attributes and functionalities with the needs of end users and in compliance with competitive offerings. These predevelopment activities provide the basis for proficiently executing the actual development activities (i.e., technical activities), and represent the efforts that enable a cooperative R&D project to position the new product as superior to competing offerings within a given market and as meaningful to potential users.

The second strongest total effect on product competitive advantage is shown by technical proficiency. High levels of technical proficiency lead to high levels of R&D objective fulfillment, and high levels of R&D objective fulfillment lead to product competitive advantage. Thus, the proficient execution of technical activities creates valuable data and information for the iterative process of R&D and thereby contributes to the fulfillment of the initial R&D objectives. Having defined the objectives of the research venture based on user preferences, market trends and “appeal” characteristics that differentiate the product, the fulfillment of the R&D objective leads to the achievement of a product competitive advantage.

In summary, this thesis contributes to the existing literature on R&D cooperations by conducting research on success of cooperative R&D projects between biotechnology firms and PRI from the perspective of achieving a product competitive advantage. The central contribution is to conceptually link success of

cooperative R&D projects between firms and PRI to achieving a product competitive advantage, which is essential to attract investors and thus to survive in the biotechnology industry (Ernst & Young 2013, p. 317; Ernst & Young 2014, p. 118). By identifying project-related and process-related factors affecting product competitive advantage and empirically testing their relationships, the implications of the results should be interesting to both academicians and practitioners.

5.3 Practical Implications

This thesis provides new and valuable insights into how cooperative R&D projects between biotechnology firms and PRI could be designed (i.e., in terms of partner selection) and executed (i.e., in terms of conducting R&D activities) to support the achievement of a product competitive advantage. The empirical analysis has demonstrated a significant impact of having adequate resources and skills on performing marketing-related and technical activities. The competent execution of these activities is beneficial for fulfilling the objectives of the cooperative R&D venture, and, finally, leads to the development of a unique, superior and meaningful biotechnological invention (i.e., achieving a product competitive advantage).

Regarding the design of cooperative R&D projects, the empirical analysis confirmed that R&D ventures benefit from establishing a match between the project's needs and available resources and skills of the cooperation partners. This finding corresponds with the notion that cooperative R&D projects are initiated to gain access to resources and specialized knowledge, which is needed to perform the tasks of R&D (Ortiz 2013, p. 281). Thus, special attention should be paid to the appropriate (i.e., with regard to the R&D objective) selection of R&D project partners.

The findings of the empirical analysis also point out that it is important not only to conduct marketing-related activities in the process of R&D but to competently execute these various activities. This includes the proficient execution of the initial evaluation of the cooperative R&D project, the proficient

determination of desirable features that differentiate the biotechnological invention, as well as competently conducting marketing research.

In the early stages of the cooperative R&D project, special attention should be paid to the initial evaluation of the R&D project based on criteria relevant to success (e.g., feasibility, project scope, exploitation potential). In particular, the evaluation of the R&D venture's idea or objective is an important initial task in the process of R&D (Rochford 1991, p. 287; Calantone et al. 1999, p. 65; Soukhoroukova et al. 2012, p. 100). Since the initial evaluation of ideas or objectives is a relatively less costly stage in the R&D process (with regard to investments in time, money, and personnel), it is advised to manage that process in the most effective and efficient way (Rochford 1991, p. 287). R&D objectives may be very diverse with respect to their level of innovativeness, chances for successful development, degree of profitability, and so forth (Calantone et al. 1999, p. 66). R&D ventures that are characterized by high probabilities of failure should be considered for elimination before substantial investments are made and opportunity costs occur, since they might prevent other products from being developed (Calantone et al. 1999, p. 66). Negligently conducting the initial evaluation of the R&D project may result in significant investments in an R&D venture with low chances of success. This is particularly critical, as empirical research has shown that many managers are reluctant to shut down failing NPD projects with the consequence of increasing costs (Schmidt/Calantone 1998).

Special attention should also be paid to the identification and determination of desirable features, as well as characteristics that would differentiate the biotechnological invention and contribute to its sale. The introduction of new features or attributes is a common way to differentiate an invention or product from competitive offerings (Nowlis/Simonson 1996, p. 36; Mukherjee/Hoyer 2001, p. 462; Thompson et al. 2005, p. 431). However, project managers should be aware of the circumstance that too many new features can make a product overwhelming for users and difficult to use (Thompson et al. 2005, p. 431ff.). Three studies conducted by Thompson et al. (2005) showed that overly complex products do not maximize users' satisfaction but may result in "feature fatigue". Therefore, the authors suggest considering more specialized or

tailored products with a limited number of features in order to enhance user satisfaction (Thompson et al. 2005, p. 441)

Furthermore, the results suggest that R&D projects would benefit from competently conducting market research (i.e., identification of potential markets and trends, analysis of users' needs, appraisal of competitors and their products). This involves the identification of potential markets and their trends (e.g., Pavlou/Reichert 2004), which may serve as a starting point in the evaluation of users' needs and the competitive situation. Of special importance for a goal-oriented R&D process is an understanding of how potential users perceive biotechnological products, how their needs are shaped and influenced and how they select products based on their preferences (van Kleef et al. 2005, p. 182). The attempts to illuminate and understand user needs take on a key role in new product development projects (Narver et al. 2004, p. 334f.). By understanding users' needs, working on biotechnological inventions that have a low chance of success in the first instance may be avoided. In addition, it ensures that potentially successful product concepts cannot be overlooked easily. Therefore, conducting research on (potential) users' needs in the predevelopment phase represents an inexpensive approach in contrast to the risk of product failure (van Kleef et al. 2005, p. 182).

Of equal importance for a goal-oriented R&D process should be the evaluation of existing and potential competitors and the search for a favorable position the biotechnological invention might take on (Radder/Louw 1998, p. 549). Existing techniques to analyze the competitive situation include, for example, the SWOT (Strengths-Weaknesses-Opportunities-Threats) analysis (Hill/Westbrook 1997 46ff.), Porter's five forces model (Porter 2008, p. 25ff.), the SPACE (Strategic Position and Action Evaluation) matrix (Radder/Louw 1998, p. 549ff), as well as the Competitive Profile Matrix (Capps III/Glissmeyer 2012, p. 1059).

In addition to marketing-related activities, the empirical analysis demonstrated the importance of competently conducting technical activities in the R&D process. This involves the proficient execution of a preliminary technical assessment, the proficient incorporation of information in the development

process, the proficient execution of product tests, the proficient planning for industrial production, as well as constantly controlling for quality and costs.

Before starting a time-consuming development process, cooperative R&D ventures in the biotechnology industry would benefit from a preliminary technical assessment involving an appraisal regarding the feasibility of developing and manufacturing the proposed biotechnological invention (Cooper 1990, p. 52). Determining the required biotechnology techniques (OECD 2005, p. 7 ff.) serves the reduction of uncertainty and is essential before investing time and money into the development of a product that eventually might not be feasible to develop (Murmann 1994, p. 247; Verworn 2008, p. 11ff.; Florén et al. 2018, p. 420).

With regard to the actual development of the proposed biotechnological invention, cooperative R&D project teams would benefit from incorporating the information gained through market research (i.e., information about potential markets and trends, users' preferences, and competitors). Research on industrial NPD showed that organizations do not always use the information they have gathered. For instance, Ottum/Moore (1997) found a strong association between product success and information use. In 80 percent of the product successes surveyed, the ventures ultimately had and used an above-average amount of market information. In 75 percent of the product failures, the project team knew less than the average amount of market information during the development project (Ottum/Moore 1997, p. 258). Thus, information about markets and trends, users' preferences, and competitors may be considered as a basis for decision making to support the development of a meaningful and superior product (Zahay et al. 2004, p. 657ff.; Veldhuizen et al. 2006, p. 353ff.)

Given the importance of technical activities in the R&D process, the proficient execution of laboratory and prototype tests, elaborating plans for industrial production, as well as quality and costs control must not be neglected as well. These activities involve an understanding of who the potential users are, what their values are, what the key technologies are and how they can be used to meet users' expectations (Kumar/Boyle 2001, p. 337ff.) and thus are closely related to the aforementioned marketing activities.

Overall, this thesis contributes to managerial practice by investigating the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. The relative importance of the factors leading to product competitive advantage suggested some important insights for managers seeking to support their research and product development process. Managers should be aware that there is no one plan which will guarantee the success of NPD or cooperative R&D ventures (Song et al. 1997b). Nevertheless, the empirical analysis suggests that improved management of the factors discussed above will increase the chances of success. Therefore, the implication presented in this section might be of considerable value and interest to executives faced with the complex task of managing cooperative R&D projects between biotechnology firms and PRI.

5.4 Limitations and Future Research Avenues

While this thesis provides several important contributions to the literature and sheds light on the determinants of success of cooperative R&D projects between biotechnology firms and PRI from a product competitive advantage perspective, the conclusions must be qualified in several ways. This section addresses limitations in combination with suggestions for future research directions.

First, as with any study, the results of this thesis must be taken into account in terms of the research method and the respective data sample (Brutus et al. 2013, p. 48ff.). This thesis involved a cross-sectional study (i.e., surveys completed by a single respondent at a single time; Rindfleisch et al. 2008, p. 262). In certain situations, cross-sectional research is considered to be sensitive to common method variance bias and questioned with regard to causal inference (Lindell/Whitney 2001, p. 114; Rindfleisch et al. 2008, p. 262). Common method variance bias refers to “systematic method error due to the use of a single rater or single source” (Rindfleisch et al. 2008, p. 261). Sources of common method variance bias may be, for instance, transient states (e.g., moods) or response styles (e.g., answering questionnaire items in a consistent fashion; Podsakoff/Organ 1986, p. 534). Such states or response styles might potentially lead to artificial relationships between variables and their outcome (Rindfleisch et al. 2008, p. 263). In order to minimize common method variance bias concerns in the survey

of this thesis respondents were offered anonymity and confidentiality to reduce socially desirable responses (i.e., answering questions in a consistent manner) (Slotegraaf/Atuahene-Gima 2011, p. 100).

Causal inference refers to "the ability to infer causation from observed empirical relations" (Rindfleisch et al. 2008, p. 261). Causal investigations are a common component of empirical studies in the realm of marketing and management research (Mackie 1965, p. 262; Rindfleisch et al. 2008, p. 263). A prerequisite of causal inferences is a chronological sequence between cause and effect (Granger 1980, p. 329ff.; Einhorn/Hogarth 1986, p. 3ff.; Rindfleisch et al. 2008, p. 263). A widespread assumption is that cross-sectional research has a limited ability to identify causal relationships because it does not capture temporal order by assessing the dependent variables at a time subsequent to its cause (Zhou et al. 2005, p. 55; Griffith/Lusch 2007, p. 141; Rindfleisch et al. 2008, p. 264). However, surveys in NPD and in the present investigation of cooperative R&D projects assess projects which inherit a natural temporal order between a cause (e.g., proficiency in executing technical activities) and its effect (e.g. product competitive advantage) that can be captured by a cross-sectional research design (Rindfleisch et al. 2008, p. 264).

Nevertheless, future research on cooperative R&D projects between biotechnology firms and PRI and the achievement of a product competitive advantage might benefit from applying longitudinal data collection methods through in-depth case studies of individual R&D projects. "Longitudinal data comprise repeated observations over time on each of many individuals" (Zeger/Liang 1992, p. 1825). Therefore, conducting research by investigating longitudinal data is a solution to reduce common method variance bias and enhancing causal inference (Rindfleisch et al. 2008, p. 262). Longitudinal studies, though, require considerable further time and financial (e.g., in the form of human resources) investments, and may suffer from a reduction in sample size due to the fluctuation of respondents. "Consequently, longitudinal survey research is easier to advocate than to implement" (Rindfleisch et al. 2008, p. 262).

Second, the data collected on cooperative R&D projects between biotechnology firms and PRI are retrospective in nature (Miller et al. 1997), with

the possibility that respondents' memories of the project may be distorted. In order to address this potential limitation at an early stage, respondents were asked to give an assessment of how knowledgeable they were in answering the questions during the survey. For the empirical evaluation, only data of respondents with a high degree of reported knowledgeability were included.

Future research might also be exposed to the problem of retrospective data, as it is difficult at the project level to obtain data from sources other than surveys (e.g. databases) (Rindfleisch et al. 2008, p. 262). In order to counteract a possible distortion of the interviewees' recollections, the use of a longitudinal study methodology (Pettigrew 1990; Rindfleisch et al. 2008), in which data are collected at different points in time in the cooperative R&D project, can be regarded as a potential solution in this issue as well.

Third, the method of questioning key informants was used in this study, which is a common approach when conducting surveys at the project-level (e.g., Veldhuizen et al. 2006). Although the respondents were knowledgeable of the cooperative R&D project they were reporting about, future research could provide further valuable insights into the achievement of a product competitive advantage in such ventures if multiple participants with different functional backgrounds were interviewed for each R&D project.

Fourth, future research could extend the developed research model by incorporating additional factors that impact the achievement of a product competitive advantage in cooperative R&D projects between biotechnology firms and PRI. Besides focusing on the factors on the project-level, factors on the level of the organization (i.e., the firm and/or the PRI) could also be considered for investigation. Organizational factors, such as organizational culture, might interact with project-level determinants of product competitive advantage.

Fifth, future research might consider the environmental context as a moderator variable in research on determinants of success of cooperative R&D projects between biotechnology firms and PRI. R&D ventures in the biotechnology industry involve new and unexplored fields of research and may, therefore, be confronted with environmental uncertainties. Environmental

uncertainties include technological and market uncertainty (Chen et al. 2012, p. 292). Technological uncertainty refers to "the inability to completely understand or accurately predict some aspect of the technological environment as it relates to NPD project decisions" (Song/Montoya-Weiss 2001, p. 64). Sources of technological uncertainty include, for example, technological newness (Shenhar et al. 2002), complexity of technology (Shenhar 1993), the rate at which technology changes in an industry (Chen et al. 2012), and lack of understanding the underlying scientific know-how (Song/Montoya-Weiss 2001). Market uncertainty can be understood as the inability to completely understand or accurately predict some aspect of the market environment as it relates to NPD project decisions. Sources of market uncertainty include, for example, market newness (Tatikonda/Montoya-Weiss 2001), instability of markets (Bstieler 2005), unpredictability of competitors, and the rate at which products are getting obsolete in an industry (Miller/Dröge 1986).

Finally, this thesis focused on cooperative R&D projects in a science-based industry (i.e., biotechnology industry). Science-based industries are characterized by complexity, interdisciplinarity, and a heavy reliance on scientific expertise (Ortiz 2013, p. 281ff.). Future research should extend the study to other science-based enabling technological industries, such as the nanotechnology industry (Niosi/Reid 2007; Nikulainen/Palmberg 2010). Of particular interest would be to investigate the developed model and its path relations in the context of other science-based industries, and thus to evaluate the model's generalizability across different technological disciplines. Understanding the achievement of a product competitive advantage in cooperative R&D projects between PRI and firms of different science-based industries could provide a useful benchmark for managerial decisions in those emerging industries. The respective findings may be of considerable value and interest to executives faced with the complex task of managing such R&D ventures.

References

Ahn, S. I. (1995). A new program in cooperative research between academia and industry in Korea, involving centers of excellence. Technovation, 15(4), 241-257.

Alvesson, M., & Kärreman, D. (2007). Constructing mystery: empirical matters in theory development. Academy of Management Review, 32(4), 1265-1281.

Arranz, N., & de Arroyabe, J. C. (2008). The choice of partners in R&D cooperation: An empirical analysis of Spanish firms. Technovation, 28(1-2), 88-100.

Arza, V., & López, A. (2011). Firms' linkages with public research organisations in Argentina: Drivers, perceptions and behaviours. Technovation, 31(8), 384-400.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the Academy of Marketing Science, 16(1), 74-94.

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. Journal of the Academy of Marketing Science, 40(1), 8-34.

Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: Does the composition of the top team make a difference?. Strategic Management Journal, 10(S1), 107-124.

Barge-Gil, A. (2010). Cooperation-based innovators and peripheral cooperators: An empirical analysis of their characteristics and behavior. Technovation, 30(3), 195-206.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

Barney, J. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. Journal of Management, 27(6), 643-650.

Barney, J., Wright, M., & Ketchen Jr, D. J. (2001). The resource-based view of the firm: Ten years after 1991. Journal of Management, 27(6), 625-641.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173-1182.

Barroso, C., Carrión, G. C., & Roldán, J. L. (2010). Applying maximum likelihood and PLS on different sample sizes: Studies on SERVQUAL model and employee behavior model. In Handbook of partial least squares, 427-447.

Bellefeuille, G. L. (2006). Rethinking reflective practice education in social work education: A blended constructivist and objectivist instructional design strategy for a web-based child welfare practice course. Journal of Social Work Education, 42(1), 85-103.

Bhatt, G. D. (2000). A resource-based perspective of developing organizational capabilities for business transformation. Knowledge and Process Management, 7(2), 119-129.

BIOCOM AG (2015). The German biotechnology sector: Facts & figures.

BIOCOM AG (2017). The German biotechnology sector: Facts & figures.

Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings, and future directions. Academy of Management Review, 20(2), 343-378.

Brush, T. H., & Artz, K. W. (1999). Toward a contingent resource-based theory: The impact of information asymmetry on the value of capabilities in veterinary medicine. Strategic Management Journal, 20(3), 223-250.

Brutus, S., Aguinis, H., & Wassmer, U. (2013). Self-reported limitations and future directions in scholarly reports: Analysis and recommendations. Journal of Management, 39(1), 48-75.

Bryman, A. (1984). The debate about quantitative and qualitative research: a question of method or epistemology?. British Journal of Sociology, 35(1), 75-92.

Bstieler, L. (2005). The moderating effect of environmental uncertainty on new product development and time efficiency. Journal of Product Innovation Management, 22(3), 267-284.

Calantone, R. J., Di Benedetto, C. A., & Schmidt, J. B. (1999). Using the analytic hierarchy process in new product screening. The Journal of Product Innovation Management, 16(1), 65-76.

Calantone, R. J., Schmidt, J. B., & Song, X. M. (1996). Controllable factors of new product success: A cross-national comparison. Marketing Science, 15(4), 341-358.

Capps III, C. J., & Glissmeyer, M. D. (2012). Extending the competitive profile matrix using internal factor evaluation and external factor evaluation matrix concepts. Journal of Applied Business Research, 28(5), 1059-1062.

Cassiman, B., Di Guardo, M. C., & Valentini, G. (2010). Organizing links with science: Cooperate or contract?: A project-level analysis. Research Policy, 39(7), 882-892.

Cattani, G., Ferriani, S., Frederiksen, L., & Täube, F. (2011). Project-based organizing and strategic management: A long-term research agenda on

temporary organizational forms. In project-based organizing and strategic management, xv-xxxix.

Chen, J., Reilly, R. R., & Lynn, G. S. (2012). New product development speed: Too much of a good thing?. Journal of Product Innovation Management, 29(2), 288-303.

Chin, W. W. (1998a). Issues and opinion on structural equation modeling. MIS Quarterly, 22(1), vii-xvi.

Chin, W. W. (1998b). The partial least squares approach to structural equation modeling. Modern Methods for Business Research, 295(2), 295-336.

Chin, W. W. (2010). How to write up and report PLS analyses. In Handbook of Partial Least Squares, 655-690.

Chin, W. W., & Dibbern, J. (2010). An introduction to a permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In Handbook of partial least squares, 171-193.

Chun, H., & Mun, S. B. (2012). Determinants of R&D cooperation in small and medium-sized enterprises. Small Business Economics, 39(2), 419-436.

Churchill Jr, G. A. (1979). A paradigm for developing better measures of marketing constructs. Journal of Marketing Research, 16(1), 64-73.

Coff, R. W. (1997). Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. Academy of Management Review, 22(2), 374-402.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128-152.

Colquitt, J. A., & Zapata-Phelan, C. P. (2007). Trends in theory building and theory testing: A five-decade study of the Academy of Management Journal. Academy of Management Journal, 50(6), 1281-1303.

Conlon, E. (2002). Editor's comments. Academy of Management Review, 27(4), 489-492.

Cooper, R. G. (1975). Why new industrial products fail. Industrial Marketing Management, 4(6), 315-326.

Cooper, R. G. (1979a). Identifying industrial new product success: Project NewProd. Industrial Marketing Management, 8(2), 124-135.

Cooper, R. G. (1979b). The dimensions of industrial new product success and failure. Journal of Marketing, 43(3), 93-103.

Cooper, R. G. (1990). Stage-gate systems: A new tool for managing new products. Business Horizons, 33(3), 44-54.

Cooper, R. G., & Kleinschmidt, E. J. (1987). New products: What separates winners from losers?. Journal of Product Innovation Management, 4(3), 169-184.

Cooper, R. G., & Kleinschmidt, E. J. (1993). Major new products: What distinguishes the winners in the chemical industry?. Journal of Product Innovation Management, 10(2), 90-111.

Corley, K. G., & Gioia, D. A. (2011). Building theory about theory building: What constitutes a theoretical contribution?. Academy of Management Review, 36(1), 12-32.

Crotty, M. (1998). The foundations of social research: Meaning and perspective in the research process. SAGE Publications.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. Management Science, 32(5), 554-571.

Daft, R. L., & Weick, K. E. (1984). Toward a model of organizations as interpretation systems. Academy of Management Review, 9(2), 284-295.

Day, G. S. (1994). The capabilities of market-driven organizations. Journal of Marketing, 58(4), 37-52.

Day, G. S., & Wensley, R. (1988). Assessing advantage: A framework for diagnosing competitive superiority. The Journal of Marketing, 52(2), 1-20.

De Faria, P., Lima, F., & Santos, R. (2010). Cooperation in innovation activities: The importance of partners. Research Policy, 39(8), 1082-1092.

De Luca, L. M., Verona, G., & Vicari, S. (2010). Market orientation and R&D effectiveness in high-technology firms: An empirical investigation in the biotechnology industry. Journal of Product Innovation Management, 27(3), 299-320.

Devlin, J. P. (1997). High throughput screening: The discovery of bioactive substances. CRC Press.

Dibbern, J., & Chin, W. W. (2005). Multi-group comparison: Testing a PLS model on the sourcing of application software services across Germany and the USA using a permutation based algorithm. In Handbuch PLS-Pfadmodellierung. Methode, Anwendung, Praxisbeispiele, 135-160.

Dijkstra, T. K. (2010). Latent variables and indices: Herman Wold's basic design and partial least squares. In Handbook of partial least squares, 23-46.

DiMasi, J. A., Grabowski, H. G., & Hansen, R. W. (2016). Innovation in the pharmaceutical industry: New estimates of R&D costs. Journal of Health Economics, 47, 20-33.

DiMasi, J. A., Hansen, R. W., & Grabowski, H. G. (2003). The price of innovation: New estimates of drug development costs. Journal of Health Economics, 22(2), 151-185.

Dormann, C. F., Elith, J., Bacher, S., et al. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography, 36(1), 27-46.

Draulans, J., de Man, A. P., & Volberda, H. (2003). Building alliance capability: Management techniques for superior alliance performance. Long Range Planning, 36(2), 151-166.

Drucker, P. F. (1988). The coming of the new organization. Harvard Business Review, 66, 45-53.

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. Academy of Management Review, 23(4), 660-679.

Einhorn, H. J., & Hogarth, R. M. (1986). Judging probable cause. Psychological Bulletin, 99(1), 3-19.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they?. Strategic Management Journal, 21(10-11), 1105-1121.

Eisenhardt, K. M., & Schoonhoven, C. B. (1996). Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms. Organization Science, 7(2), 136-150.

Egelhoff, W. G. (1991). Information-processing theory and the multinational enterprise. Journal of International Business Studies, 22(3) 341-368.

Ernst & Young (2013). Umdenken… weiter denken, breiter denken. Deutscher Biotechnologie-Report 2013. Ernst & Young, Mannheim.

Ernst & Young (2014). 1% für die Zukunft – Innovation zum Erfolg bringen. Deutscher Biotechnologie-Report 2014. Ernst & Young, Mannheim.

Faems, D., Van Looy, B., & Debackere, K. (2005). Interorganizational collaboration and innovation: Toward a portfolio approach. Journal of Product Innovation Management, 22(3), 238-250.

Farrell, A. M. (2010). Insufficient discriminant validity: A comment on Bove, Pervan, Beatty, and Shiu (2009). Journal of Business Research, 63(3), 324-327.

Field, A., Miles, J., & Field, Z. (2012). Discovering statistics using R. SAGE Publications.

Florén, H., Frishammar, J., Parida, V., & Wincent, J. (2018). Critical success factors in early new product development: A review and a conceptual model. International Entrepreneurship and Management Journal, 14(2), 411-427.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Galbraith, J. R. (1973). Designing complex organizations. Addison-Wesley Longman Publishing Co., Inc..

Galbraith, J. R. (1974). Organization design: An information processing view. Interfaces, 4(3), 28-36.

Geisser, S. (1974). A predictive approach to the random effects model. Biometrika, 61(1), 101–107.

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2010). Evaluation of structural equation models using the partial least squares (PLS) approach. In Handbook of partial least squares, 691-711.

Granger, C. W. (1980). Testing for causality: A personal viewpoint. Journal of Economic Dynamics and Control, 2(1), 329-352.

Gray, P. H. (2000). The effects of knowledge management systems on emergent teams: Towards a research model. The Journal of Strategic Information Systems, 9(2), 175-191.

Griffith, D. A., & Lusch, R. F. (2007). Getting marketers to invest in firm-specific capital. Journal of Marketing, 71(1), 129-145.

Guba, E. G. (1990). The alternative paradigm dialog. In The paradigm dialog, 17-30.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). SAGE Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139-152.

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). European Business Review, 26(2), 106-121.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. Long Range Planning, 45(5-6), 320-340.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science, 40(3), 414-433.

Hall, B. H., Link, A. N., & Scott, J. T. (2003). Universities as research partners. Review of Economics and Statistics, 85(2), 485-491.

Harmancioglu, N., Droge, C., & Calantone, R. J. (2009). Strategic fit to resources versus NPD execution proficiencies: What are their roles in determining success?. Journal of the Academy of Marketing Science, 37(3), 266-282.

Heide, J. B., & John, G. (1990). Alliances in industrial purchasing: The determinants of joint action in buyer-supplier relationships. Journal of Marketing Research, 27(1), 24-36.

Heide, J. B., & Miner, A. S. (1992). The shadow of the future: Effects of anticipated interaction and frequency of contact on buyer-seller cooperation. Academy of Management Journal, 35(2), 265-291.

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. Structural Equation Modeling, 17(1), 82-109.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405-431.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. Advances in International Marketing, 20, 277-319.

Hill, T., & Westbrook, R. (1997). SWOT analysis: It's time for a product recall. Long Range Planning, 30(1), 46-52.

Hitt, M. A., & Smith, K. G. 2005. Introduction: The process of developing management theory. In Great minds in management: The process of theory development, 1-6.

Hoe, S. L. (2008). Issues and procedures in adopting structural equation modeling technique. Journal of Applied Quantitative Methods, 3(1), 76-83.

Honek, J. (2017). Preclinical research in drug development. Medical Writing, 26(4), 5-8.

Horn, J. L., & McArdle, J. J. (1992). A practical and theoretical guide to measurement invariance in aging research. Experimental Aging Research, 18(3), 117-144.

Hughes, J. A., & Sharrock, W. W. (2016). The philosophy of social research. Routledge.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic Management Journal, 20(2), 195-204.

Hult, G. T. M., Ketchen, D. J., Griffith, D. A., Finnegan, C. A., Gonzalez-Padron, T., Harmancioglu, N., ... & Cavusgil, S. T. (2008). Data equivalence in cross-cultural international business research: Assessment and guidelines. Journal of International Business Studies, 39(6), 1027-1044.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research, 30(2), 199-218.

Keller, R. T. (1994). Technology-information processing fit and the performance of R&D project groups: A test of contingency theory. Academy of Management Journal, 37(1), 167-179.

Kock, N. (2014). Stable P value calculation methods in PLS-SEM. Laredo, TX: ScriptWarp Systems.

Koza, M. P., & Lewin, A. Y. (1998). The co-evolution of strategic alliances. Organization Science, 9(3), 255-264.

Kumar, N., Stern, L. W., & Anderson, J. C. (1993). Conducting interorganizational research using key informants. Academy of Management Journal, 36(6), 1633-1651.

Kumar, V., & Boyle, T. (2001). A quality management implementation framework for manufacturing-based R&D environments. International Journal of Quality & Reliability Management, 18(3), 336-359.

Lado, A. A., Boyd, N. G., & Wright, P. (1992). A competency-based model of sustainable competitive advantage: Toward a conceptual integration. Journal of Management, 18(1), 77-91.

Langerak, F., Hultink, E. J., & Robben, H. S. (2004). The impact of market orientation, product advantage, and launch proficiency on new product performance and organizational performance. Journal of Product Innovation Management, 21(2), 79-94.

Lee, L., Petter, S., Fayard, D., & Robinson, S. (2011). On the use of partial least squares path modeling in accounting research. International Journal of Accounting Information Systems, 12(4), 305-328.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. Strategic Management Journal, 14(S2), 95-112.

Li, T., & Calantone, R. J. (1998). The impact of market knowledge competence on new product advantage: Conceptualization and empirical examination. Journal of Marketing, 62(4), 13-29.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. Journal of Applied Psychology, 86(1), 114-121.

MacCallum, R. C., & Browne, M. W. (1993). The use of causal indicators in covariance structure models: Some practical issues. Psychological Bulletin, 114(3), 533-541.

Mackie, J. L. (1965). Causes and conditions. American Philosophical Quarterly, 2(4), 245-264.

McDonald, R. P., & Ho, M. H. R. (2002). Principles and practice in reporting structural equation analyses. Psychological Methods, 7(1), 64-82.

McMillan, G. S., Narin, F., & Deeds, D. L. (2000). An analysis of the critical role of public science in innovation: The case of biotechnology. Research Policy, 29(1), 1-8.

McNally, R. C., Cavusgil, E., & Calantone, R. J. (2010). Product innovativeness dimensions and their relationships with product advantage, product financial performance, and project protocol. Journal of Product Innovation Management, 27(7), 991-1006.

Mestre-Ferrandiz, J., Sussex, J., & Towse, A. (2012). The R&D cost of a new medicine. Monographs, Office of Health Economics, London.

Midi, H., Sarkar, S. K., & Rana, S. (2010). Collinearity diagnostics of binary logistic regression model. Journal of Interdisciplinary Mathematics, 13(3), 253-267.

Miller, C. C., Cardinal, L. B., & Glick, W. H. (1997). Retrospective reports in organizational research: A reexamination of recent evidence. Academy of Management Journal, 40(1), 189-204.

Miller, D., & Dröge, C. (1986). Psychological and traditional determinants of structure. Administrative Science Quarterly, 31(4), 539-560.

Millson, M. R., & Wilemon, D. (2008). Impact of new product development (NPD) proficiency and NPD entry strategies on product quality and risk. R&D Management, 38(5), 491-509.

Miotti, L., & Sachwald, F. (2003). Co-operative R&D: why and with whom?: An integrated framework of analysis. Research Policy, 32(8), 1481-1499.

Mitroff, I. I. (1982). Talking past one's colleagues in matters of policy. Strategic Management Journal, 3(4), 374-376.

Moenaert, R. K., & Souder, W. E. (1990). An information transfer model for integrating marketing and R&D personnel in new product development projects. Journal of Product Innovation Management, 7(2), 91-107.

Moon, K., & Blackman, D. (2014). A guide to understanding social science research for natural scientists. Conservation Biology, 28(5), 1167-1177.

Mora-Valentin, E. M., Montoro-Sanchez, A., & Guerras-Martin, L. A. (2004). Determining factors in the success of R&D cooperative agreements between firms and research organizations. Research Policy, 33(1), 17-40.

Mukherjee, A., & Hoyer, W. D. (2001). The effect of novel attributes on product evaluation. Journal of Consumer Research, 28(3), 462-472.

Müller, C. (2007). Die frühen Innovationsphasen in der Biotechnologie. In Management der frühen Innovationsphasen, 383-404.

Murmann, P. A. (1994). Expected development time reductions in the German mechanical engineering industry. Journal of Product Innovation Management, 11(3), 236-252.

Nakata, C., Im, S., Park, H., & Ha, Y. W. (2006). Antecedents and consequence of Korean and Japanese new product advantage. Journal of Business Research, 59(1), 28-36.

Narver, J. C., Slater, S. F., & MacLachlan, D. L. (2004). Responsive and proactive market orientation and new-product success. Journal of Product Innovation Management, 21(5), 334-347.

Nikulainen, T., & Palmberg, C. (2010). Transferring science-based technologies to industry - Does nanotechnology make a difference?. Technovation, 30(1), 3-11.

Niosi, J., & Reid, S. E. (2007). Biotechnology and nanotechnology: Science-based enabling technologies as windows of opportunity for LDCs?. World Development, 35(3), 426-438.

Nowlis, S. M., & Simonson, I. (1996). The effect of new product features on brand choice. Journal of Marketing Research, 18(1), 36-46.

Nunnally, J.C. (1978). Psychometric Theory. McGraw-Hill.

OECD (2005). A framework for biotechnology statistics, http://www.oecd.org/sti/inno/34935605.pdf [15.12.2013].

Okamuro, H., Kato, M., & Honjo, Y. (2011). Determinants of R&D cooperation in Japanese start-ups. Research Policy, 40(5), 728-738.

Ortiz, A. (2013). Kooperation zwischen Unternehmen und Universitäten: Eine Managementperspektive zur Kooperation zwischen Unternehmen und Universitäten in regionalen Innovationssystemen. Zugl. Dissertation, Otto-Friedrich-Universität Bamberg, 2012. Springer Fachmedien.

Ottum, B. D., & Moore, W. L. (1997). The role of market information in new product success/failure. Journal of Product Innovation Management, 14(4), 258-273.

Owen-Smith, J., & Powell, W. W. (2003). The expanding role of university patenting in the life sciences: Assessing the importance of experience and connectivity. Research Policy, 32(9), 1695-1711.

Parry, M. E., & Song, X. M. (1994). Identifying new product successes in China. Journal of Product Innovation Management, 11(1), 15-30.

Paul, S. M., Mytelka, D. S., Dunwiddie, C. T., Persinger, C. C., Munos, B. H., Lindborg, S. R., & Schacht, A. L. (2010). How to improve R&D productivity: The pharmaceutical industry's grand challenge. Nature Reviews Drug Discovery, 9(3), 203.

Pavlou, A. K., & Reichert, J. M. (2004). Recombinant protein therapeutics - success rates, market trends and values to 2010. Nature Biotechnology, 22(12), 1513-1519.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. Journal of Operations Management, 30(6), 467-480.

Penrose, E. G. (1959). The theory of the growth of the firm. Wiley.

Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. Strategic Management Journal, 14(3), 179-191.

Peteraf, M. A., & Barney, J. B. (2003). Unraveling the resource-based tangle. Managerial and Decision Economics, 24(4), 309-323.

Peters, M. (2008). Vertrauen in Wertschöpfungspartnerschaften zum Transfer von retentivem Wissen: Eine Analyse auf Basis realwissenschaftlicher Theorien und Operationalisierung mithilfe des Fuzzy Analytic Network Process und der Data Envelopment Analysis. Zugl. Dissertation Universität Duisburg-Essen, Campus Essen, 2008. Gabler Verlag.

Petruzzelli, A. M. (2011). The impact of technological relatedness, prior ties, and geographical distance on university–industry collaborations: A joint-patent analysis. Technovation, 31(7), 309-319.

Pettigrew, A. M. (1990). Longitudinal field research on change: Theory and practice. Organization Science, 1(3), 267-292.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of Management, 12(4), 531-544.

Polanyi, M. (1966): The tacit dimension. Anchor Day Books.

Porter, M. E. (2008). The five competitive forces that shape strategy. Harvard Business Review, 86(1), 25-40.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. Administrative Science Quarterly, 116-145.

Pratt, D. D. (1998). Five perspectives on teaching in adult and higher education. Krieger Publishing Co.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879-891.

Radder, L., & Louw, L. (1998). The SPACE matrix: A tool for calibrating competition. Long Range Planning, 31(4), 549-559.

Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. International Journal of Research in Marketing, 26(4), 332-344.

Rijsdijk, S. A., Langerak, F., & Jan Hultink, E. (2011). Understanding a two-sided coin: Antecedents and consequences of a decomposed product advantage. Journal of Product Innovation Management, 28(1), 33-47.

Rindfleisch, A., Malter, A. J., Ganesan, S., & Moorman, C. (2008). Cross-sectional versus longitudinal survey research: Concepts, findings, and guidelines. Journal of Marketing Research, 45(3), 261-279.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). Editor's Comments: A critical look at the use of PLS-SEM in "MIS Quarterly". MIS Quarterly, 36(1), iii-xiv.

Ringle, C. M., Wende, S., & Becker, J. M. (2015). SmartPLS 3. Boenningstedt: SmartPLS GmbH, http://www. smartpls. com.

Robinson, D. T., & Stuart, T. E. (2006). Network effects in the governance of strategic alliances. The Journal of Law, Economics, & Organization, 23(1), 242-273.

Rochford, L. (1991). Generating and screening new products ideas. Industrial Marketing Management, 20(4), 287-296.

Rogers, P. R., Miller, A., & Judge, W. Q. (1999). Using information-processing theory to understand planning/performance relationships in the context of strategy. Strategic Management Journal, 20(6), 567-577.

Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and exploitation alliances in biotechnology: A system of new product development. Strategic Management Journal, 25(3), 201-221.

Rumelt, R. P., Schendel, D., & Teece, D. J. (1991). Strategic management and economics. Strategic Management Journal, 12(S2), 5-29.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. Advances in International Marketing, 22, 195-218.

Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). Long Range Planning, 47(3), 154-160.

Sarstedt, M., Schwaiger, M., & Ringle, C. M. (2009). Do we fully understand the critical success factors of customer satisfaction with industrial goods?- Extending Festge and Schwaiger's model to account for unobserved heterogeneity. Journal of Business Market Management, 3(3), 185-206.

Saxton, T. (1997). The effects of partner and relationship characteristics on alliance outcomes. Academy of Management Journal, 40(2), 443-461.

Schmidt, J. B., & Calantone, R. J. (1998). Are really new product development projects harder to shut down?. The Journal of Product Innovation Management, 15(2), 111-123.

Schüler, J. (2016). Die Biotechnologie-Industrie: Ein Einführungs-, Übersichts- und Nachschlagewerk. Springer Spektrum.

Schultz, C. (2006). Management hochwertiger Dienstleistungen: Erfolgreiche Gestaltung von Kundenbeziehungen am Beispiel der Telemedizin. Zugl. Dissertation Technische Universität Berlin, 2006. Gabler Verlag.

Schwartz, M., Peglow, F., Fritsch, M., & Günther, J. (2012). What drives innovation output from subsidized R&D cooperation?—Project-level evidence from Germany. Technovation, 32(6), 358-369.

Shenhar, A. J. (1993). From low-to high-tech project management. R&D Management, 23(3), 199-214.

Shenhar, A. J., Dvir, D., Levy, O., & Maltz, A. C. (2001). Project success: A multidimensional strategic concept. Long Range Planning, 34(6), 699-725.

Shenhar, A. J., Tishler, A., Dvir, D., Lipovetsky, S., & Lechler, T. (2002). Refining the search for project success factors: a multivariate, typological approach. R&D Management, 32(2), 111-126.

Simonin, B. L. (1999a). Ambiguity and the process of knowledge transfer in strategic alliances. Strategic Management Journal, 20(7), 595-623.

Simonin, B. L. (1999b). Transfer of marketing know-how in international strategic alliances: An empirical investigation of the role and antecedents of knowledge ambiguity. Journal of International Business Studies, 30(3), 463-490.

Sinkula, J. M. (1994). Market information processing and organizational learning. Journal of Marketing, 58(1), 35-45.

Slotegraaf, R. J., & Atuahene-Gima, K. (2011). Product development team stability and new product advantage: The role of decision-making processes. Journal of Marketing, 75(1), 96-108.

Song, X. M., & Montoya-Weiss, M. M. (2001). The effect of perceived technological uncertainty on Japanese new product development. Academy of Management Journal, 44(1), 61-80.

Song, X. M., Montoya-Weiss, M. M., & Schmidt, J. B. (1997a). The role of marketing in developing successful new products in South Korea and Taiwan. Journal of International Marketing, 5(3), 47-69.

Song, X. M., & Parry, M. E. (1996). What separates Japanese new product winners from losers. Journal of Product Innovation Management, 13(5), 422-439.

Song, X. M., & Parry, M. E. (1997a). A cross-national comparative study of new product development processes: Japan and the United States. The Journal of Marketing, 61(2), 1-18.

Song, X. M., & Parry, M. E. (1997b). The determinants of Japanese new product successes. Journal of Marketing Research, 34(1), 64-76.

Song, X. M., & Parry, M. E. (1999). Challenges of managing the development of breakthrough products in Japan. Journal of Operations Management, 17(6), 665-688.

Song, X. M., Souder, W. E., & Dyer, B. (1997b). A causal model of the impact of skills, synergy, and design sensitivity on new product performance. Journal of Product Innovation Management, 14(2), 88-101.

Song, X. M., Van Der Bij, H., & Weggeman, M. (2005). Determinants of the level of knowledge application: A knowledge-based and information-processing perspective. Journal of Product Innovation Management, 22(5), 430-444.

Souder, W. E., Buisson, D., & Garrett, T. (1997). Success through customer-driven new product development: A comparison of US and New Zealand small entrepreneurial high technology firms. Journal of Product Innovation Management, 14(6), 459-472.

Soukhoroukova, A., Spann, M., & Skiera, B. (2012). Sourcing, filtering, and evaluating new product ideas: An empirical exploration of the performance of idea markets. Journal of Product Innovation Management, 29(1), 100-112.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society, 36(2), 111–147.

Stuart, T. E., & Ding, W. W. (2006). When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. American Journal of Sociology, 112(1), 97-144.

Stuart, T. E., Ozdemir, S. Z., & Ding, W. W. (2007). Vertical alliance networks: The case of university–biotechnology–pharmaceutical alliance chains. Research Policy, 36(4), 477-498.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. Strategic Management Journal, 17(2), 27-43.

Tatikonda, M. V., & Montoya-Weiss, M. M. (2001). Integrating operations and marketing perspectives of product innovation: The influence of organizational process factors and capabilities on development performance. Management Science, 47(1), 151-172.

Tether, B. S. (2002). Who co-operates for innovation, and why: An empirical analysis. Research Policy, 31(6), 947-967.

Thompson, D. V., Hamilton, R. W., & Rust, R. T. (2005). Feature fatigue: When product capabilities become too much of a good thing. Journal of Marketing Research, 42(4), 431-442.

Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. Academy of Management Review, 3(3), 613-624.

Van Kleef, E., Van Trijp, H. C., & Luning, P. (2005). Consumer research in the early stages of new product development: A critical review of methods and techniques. Food Quality and Preference, 16(3), 181-201.

Veldhuizen, E., Hultink, E. J., & Griffin, A. (2006). Modeling market information processing in new product development: An empirical analysis. Journal of Engineering and Technology Management, 23(4), 353-373.

Verworn, B., Herstatt, C., & Nagahira, A. (2008). The fuzzy front end of Japanese new product development projects: Impact on success and differences between incremental and radical projects. R&D Management, 38(1), 1-19.

Weiber, R., & Mühlhaus, D. (2014). Strukturgleichungsmodellierung: Eine anwendungsorientierte Einführung in die Kausalanalyse mit Hilfe von AMOS, SmartPLS und SPSS. Springer-Verlag.

Weise, J. (2007). Planung und Steuerung von Innovationsprojekten. Dissertation Technische Universität Berlin, 2007. Deutscher Universitätsverlag.

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic Management Journal, 5(2), 171-180.

Whetten, D. (1990). Editor's comment. Academy of Management Review, 15(4), 578-583.

Wold, H. (1974). Causal flows with latent variables: partings of the ways in the light of NIPALS modelling. European Economic Review, 5(1), 67-86.

Wold, H. (1980). Model construction and evaluation when theoretical knowledge is scarce: Theory and application of partial least squares. In Evaluation of Econometric Models, 47-74.

Wold, H. (1982). Soft modeling: The basic design and some extensions. In Systems under indirect observations: Part II.

Wold, S., Ruhe, A., Wold, H., & Dunn, III, W. J. (1984). The collinearity problem in linear regression. The partial least squares (PLS) approach to generalized inverses. SIAM Journal on Scientific and Statistical Computing, 5(3), 735-743.

Yilmaz, K. (2013). Comparison of quantitative and qualitative research traditions: Epistemological, theoretical, and methodological differences. European Journal of Education, 48(2), 311-325.

Zahay, D., Griffin, A., & Fredericks, E. (2004). Sources, uses, and forms of data in the new product development process. Industrial Marketing Management, 33(7), 657-666.

Zeger, S. L., & Liang, K. Y. (1992). An overview of methods for the analysis of longitudinal data. Statistics in Medicine, 11(14-15), 1825-1839.

Zhou, K. Z., Yim, C. K., & Tse, D. K. (2005). The effects of strategic orientations on technology-and market-based breakthrough innovations. Journal of Marketing, 69(2), 42-60.

Zirger, B. J., & Maidique, M. A. (1990). A model of new product development: An empirical test. Management Science, 36(7), 867-883.

Zucker, L. G., & Darby, M. R. (2001). Capturing technological opportunity via Japan's star scientists: Evidence from Japanese firms' biotech patents and products. The Journal of Technology Transfer, 26(1-2), 37-58.

Zucker, L. G., Darby, M. R., & Armstrong, J. (1998). Geographically localized knowledge: Spillovers or markets?. Economic Inquiry, 36(1), 65-86.

Zucker, L. G., Darby, M. R., & Armstrong, J. (2002). Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. Management Science, 48(1), 138-153.

Zucker, L. G., Darby, M. R., & Brewer, M. B. (1998). Intellectual human capital and the birth of US biotechnology enterprises. American Economic Review, 88(1), 290-306.

Zucker, L. G., Darby, M. R., & Torero, M. (2002). Labor mobility from academe to commerce. Journal of Labor Economics, 20(3), 629-660.

Appendix

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