Information Requirements Analysis for Business Intelligence Systems using System Dynamics

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"PERFECTION IS ACHIEVED NOT WHEN THERE IS NOTHING MORE TO BE ADDED BUT WHEN THERE IS NOTHING LEFT TO TAKE AWAY." [1]

Antoine de Saint-Exupéry
(1900-1944)

[1] Original French citation: *"Il semble que la perfection soit atteinte non quand il n'y a plus rien à ajouter, mais quand il n'y a plus rien à retrancher"* (Saint-Exupéry 1939, p. 60), English translation follows Fitzgerald et al. (2003).

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Table of Papers

This dissertation is based on following five papers (co-)written by the author:

P.1 **Mosig, B.** (2012): Towards a Method to Improve Alignment of Objective and Subjective Information Requirements of Decision Makers - The Potential of System Dynamics for Information Requirement Analysis, published in: Proceedings of the 45th Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, January 2012, pp. 4209–4218.
VHB-JOURQUAL2.1: Category C
WI Orientation List: Category B

P.2 Meier, M.C./ **Mosig, B.**/ Reinwald, D. (2011): Entscheidungsunterstützung für ein unternehmenswertorientiertes Beschwerdemanagement im Dienstleistungsbereich durch ein dynamisches Simulationsmodell, published in: A. Bernstein, G. Schwabe, eds., Proceedings of the 10th International Conference on Wirtschaftsinformatik, Zurich, Switzerland, February 2011, pp. 160–169.
VHB-JOURQUAL2.1: Category C
WI Orientation List: Category A

P.3 **Mosig, B.**/ Reinwald, D./ Meier, M.C. (2012): Simulating the Value-Based Implications of Word-of-Mouth Effects on Customer Acquisition and Retention: A System Dynamics Approach, FIM working paper WI-394.

P.4 Gleich, B./ **Mosig, B.**/ Reinwald, D. (2011): Contributing to Knowledge-based Decision Support: A System Dynamics Model Regarding the Use of Non-Renewable Resources, published in: Proceedings of the 19th European Conference on Information Systems (ECIS), Helsinki, Finland, June 2011, paper 181.
VHB-JOURQUAL2.1: Category B
WI Orientation List: Category A

P.5 **Mosig, B.**/ Röglinger M. (2012): A Metadata-based Approach to Leveraging the Information Supply of Business Intelligence Systems, published in: P. Atzeni, D. Cheung, and R. Sudha, eds., Proceedings of the 31st International Conference on Conceptual Modeling–The Entity Relationship Approach (ER), Florence, Italy, October 2012, pp. 537–542.
VHB-JOURQUAL2.1: Category B
WI Orientation List: Category A

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Table of Abbreviations

BI	Business Intelligence
BSC	Balanced Scorecard
CE	Customer Equity
CEO	Chief Executive Officer
CLV	Customer Lifetime Value
CRM	Customer Relationship Management
DNA	Deoxyribonucleic Acid
DVD	Digital Versatile Disc
FIM	Research Center Finance & Information Management
GI	Gesellschaft für Informatik (German Association for Computer Science)
I²RDM	Identification of Information Requirements of Decision Makers (name of the method proposed in this dissertation)
IDC	International Data Corporation (global IT market data provider)
IRA	Information Requirements Analysis
IS	Information Systems
IT	Information Technology
kg	kilogram
LCD	Liquid Crystal Display
MSS	Management Support Systems
nd	no date
NoSQL	Not only SQL
OSN	Online Social Networks
ppm	parts per million
RFM	Recency-Frequency-Monetary value
SAP	Systeme, Anwendungen und Produkte in der Datenverarbeitung (German software company)
SD	System Dynamics
SQL	Structured Query Language

TARP	Technical Assistance Research Program
US	United States
USGS	United States Geological Survey
WACC	Weighted Average Cost of Capital
WOM	Word-of-Mouth
XML	Extensible Markup Language

1 Introduction

1.1 Motivation

The amount of business data is growing exponentially (Reddi et al. 2011). In 2011, worldwide a total of two zettabyte (i.e., two trillion gigabyte) has been generated, equalling a required storage capacity of 200 billion DVDs (Dambeck 2012). That pile would have a height of 240,000 km or nearly two thirds of the average distance from the earth to the moon. And the situation is continually getting worse: According to researchers of IDC, the newly added volume of data doubles every two years (Dambeck 2012; Gantz et al. 2008; Reddi et al. 2011).

Since information – understood as "data that are processed to be useful" (Ackoff (1989) cited according to Rowley (2007, p. 167)) – constitute the basis for business decision making, the resulting information proliferation and information overload are problematic phenomenon in most companies. Reasons include the complexity of managerial structures and processes, both extent and growth dynamics of potentially relevant information, the high number of simultaneous tasks, increased speed of decision-making in the so-called Internet economy as well as correspondingly high information needs (Crenshaw 2008; EMC² 2008; Eppler and Mengis 2004; The Economist 2010). But despite improvements triggered by scientific work and technological advancements, another IDC study reports that 75% of respondents still suffer from information overload (Gantz et al. 2009). Other studies indicate that about 50% of decision makers regularly face useless information (Accenture 2007; Farhoomand and Drury 2002). Typical negative consequences include mental stress, loss of clarity, and reduced decision quality (Arnott and Dodson 2008; Bawden and Robinson 2009; Eppler and Mengis 2004; Gantz et al. 2009). This accumulates to a significant negative economic impact. A Gallup study estimates the loss of productivity due to stressed employees to sum up to 300 billion US dollar in the United States (Mindjet 2008). Although this loss cannot be assigned exclusively to information overload, these figures illustrate the strong need to improve the information supply of decision makers with regard to providing the "right" amount of the "right" information.

Information requirements analysis deals with the problem of selecting those information that enable decision makers to be most effective (i.e., doing the right things with regard to a company's objectives) and most efficient (i.e., using the smallest possible amount of resources such as time, money, or employees). Numerous methods for various types of management support systems (MSS) – most recently Business Intelligence (BI) systems – have been proposed to increase the clarity in corporate decision making (Giorgini et al. 2008; Inmon 2009; Kimball et al. 2008; Stroh et al. 2011; Volonino and Watson 1991; Watson and Frolick 1993; Wetherbe 1991; Winter and Strauch 2004). A key challenge remains the prioritization of information needs (Stroh et al. 2011). Especially against the backdrop of a highly dynamic and increasingly interwoven complex environment (Dean et al. 2012; Reeves et al. 2012), decision makers struggle to cope with the richness of the real world (Sterman 2000, 2001, 2010). Sterman (2001) identifies dynamic complexity – defined as "the often counterintuitive behavior of complex systems that arises from the interactions of the agents over time" (p. 11) – as the primary root cause. He traces dynamic complexity back to a number of reasons including feedback loops (such as the mutual reinforcing dependency of investments and profit), time delays (for instance, caused by warehousing), and non-linear developments (such as the exponential growth patterns observable in the customer base of network-based business models) that characterize the real business environment. Especially in combination, dynamic complexity makes an isolated examination of a single piece of information error-prone and potentially misleading. Current methods for information requirements analysis fall short of explicitly considering these characteristics and often lack an interconnected holistic view. Already Stroh et al. (2011) refer to this issue when they state the need for a continual process to identify information requirements.

System Dynamics (SD) is both capable of providing a holistic system's perspective and of dealing with the described characteristics. The methodology helps to comprehensively identify, analyze, and simulate complex causal structures of managerial systems for the "design of improved organizational form and guiding policy" (Forrester 1969, 1971). Hence, this dissertation examines how System Dynamics can be used to improve the information requirements analysis for Business Intelligence systems.

1.2 Delineation of Research Object

Business Intelligence systems – formerly often coined analytical information systems (Chamoni and Gluchowski 2006) – are the central object of investigation since they nowadays form an essential part of information provisioning for decision makers. Varying definitions of Business Intelligence can be found emphasizing different aspects (e.g., Business Intelligence understood as a class of systems versus Business Intelligence as integrated approach for decision support) (Fachgruppe BI der GI e.V. 2011). But although a standardized definition is difficult, most share the goal of supporting managerial decision making (Eckerson 2005; Gluchowski et al. 2008; Golfarelli et al. 2004; Negash 2004; Turban et al. 2010). For the purpose of this dissertation, the definition of Negash (2004, p. 178) is adopted: "BI systems combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers."

Information proliferation and information overflow cause challenges for Business Intelligence that are currently addressed from various angles. The analysis of large data sets (big data analytics) has recently become one of the largest trends (Chamoni 2011). Big data analytics is characterized not only by a high volume of data, but also by diverse velocities (ranging from batch to real time processing) and varieties (with a higher focus on semi-structured and unstructured data) (Russom 2011). Advancements as in-memory technologies ("velocity") and NoSQL databases ("variety") are much talked and written about (Meier and Scheffler 2011; Plattner and Zeier 2011; Pospiech and Felden 2012; Russom 2011). According to Gartner's hype cycle for emerging technologies, both big data and in-memory technologies have reached the "peak of inflated expectations" in August 2012 (Pettey and Meulen 2012). Not denying the relevance of these new technologies, it is astonishing how much the focus of both researchers and practitioners shifted towards semi-structured and unstructured data. Since structured data still constitutes the largest source for managerial information provisioning (Russom 2011), the fight against information overload must also include approaches for a more efficient and effective handling of structured data. Hence, this dissertation presents new approaches to handle structured data.

The research focus is further laid on measures or (performance) indicators. Measures are defined as "a metric used to quantify the efficiency and/or effectiveness of an action" (Neely et al. 1995, p. 80). The emphasis on measures can be justified since they form *an* – if not *the* most – important part of the information supply for decision makers (Strecker et al. 2012). They are well structured, readily available from various Business Intelligence systems as data warehouses or data marts, and their amount has multiplied over the last decades (Gantz et al. 2009; The Economist 2010). On the downside, there are concerns that all relevant aspects can be captured in a measure without an unacceptable degree of bias (Moers 2005), that measures suggest a preciseness that is not matched by the real-world's fuzziness, and that they can provoke actions incoherent or even contradictory to organizational goals (Strecker et al. 2012). On the other hand, they are widely used following a "management by objectives" approach and for performance measurement (Eccles 1991). According to Neely et al. (1995) measures are well-accepted for providing decision makers with information allowing them to take effective actions. Their primary use has been seen in well-structured decision fields such as cost accounting with operational decisions based on financial information (Drucker 1995). To capture other operational decisions, concepts such as the Balanced Scorecard or Strategy Maps have been proposed that also include non-financial measures (Kaplan and Norton 1992, 2004). Thus, the majority of decisions can be assumed to be at least partly based on measures. Even for strategic decisions, measures have a supportive character (Kaplan and Norton 1992). Furthermore, measures have been identified as feasible abstraction to reduce complexity thereby avoiding information overload (Strecker et al. 2012).

Finally, to gain a shared conceptualization of information needs and related terms, the terminology for the corporate information space introduced by Winter and Strauch (2003) is presented (see Figure 1-1). It is used throughout this dissertation.

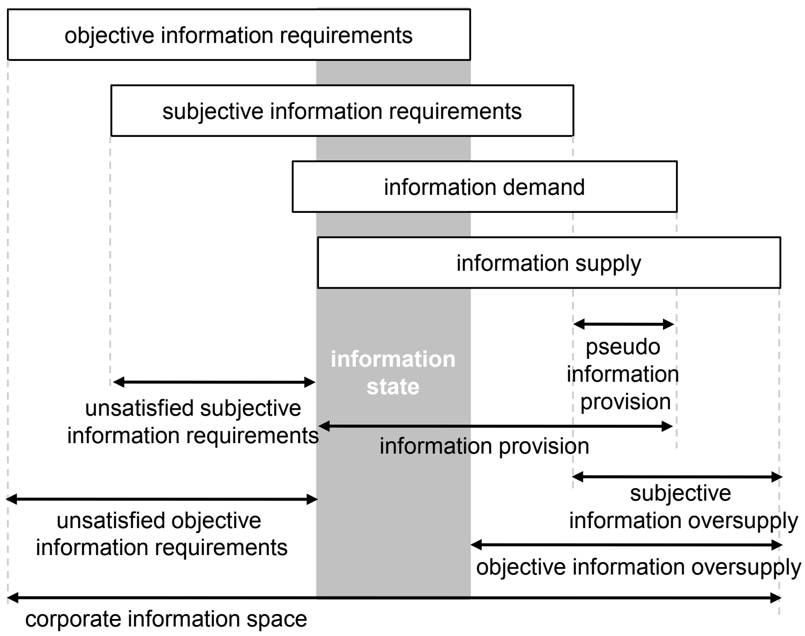

Figure 1-1: Enterprise information space (Winter and Strauch 2003, p. 3)

Information requirements are defined as "the type, amount and quality of information that a decision maker […] needs to do his/her job" (Winter and Strauch 2003, p. 3). They are task-specific, vary over time and depend on the decision maker's previous knowledge and mentality. Often, they cannot be exactly specified. "While *objective information requirements* comprise all information that actually is relevant to fulfill his/her respective tasks, *subjective information requirements* denote all information that the decision maker […] believes to be relevant" (Winter and Strauch 2003, p. 4). The *information demand* represents the articulated portion of the (subjective) information requirements whereby typically more information is requested "as a precaution or as a means of power (pseudo information provision)" (Winter and Strauch 2003, p. 4). The *information supply* is defined as "the entirety of information that is available to a decision maker […] at a certain point in time and at a certain (work)place” (Winter and Strauch 2003, p. 4). Its intersection with the information demand is the provided information (information provision). The *information state* indicates which parts of the information requirements are covered by the information supply. This is the information basis on which decision makers ground their decisions.

1.3 Objectives

To improve the information supply of decision makers with regard to providing the “right” amount of the “right” measure-based information, the idea of Meier (Meier 2007; Meier et al. 2007) to structure information requirements according to a core-shell model is adopted (see Figure 1-2). Information requirements can be classified into standardized information requirements relevant for all decision makers within a company (core), role-based information requirements relevant for specific decision makers with typical task bundles (inner shell), and user-individual information requirements (outer shell).

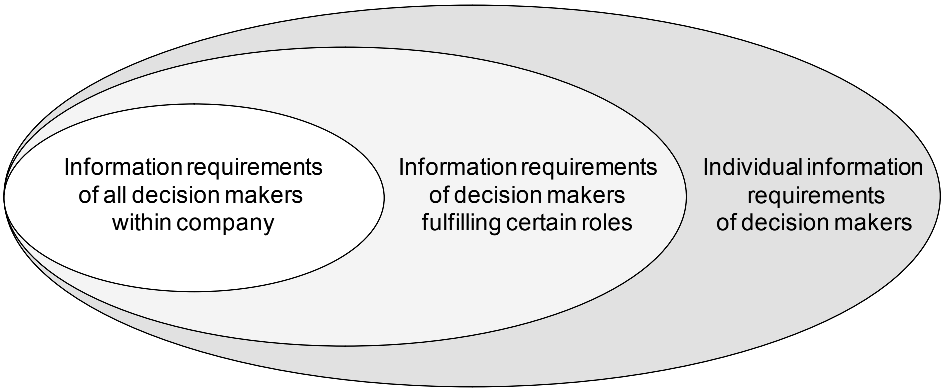

Figure 1-2: Classification of information requirements

This dissertation addresses the trade-off between too much (“information overload”) and not sufficient information by answering the research question on *“how to improve the measure-based information state of decision makers in order to reach goals?”* The research question decomposes into three objectives that are assigned to both the inner shell (objectives O1 and O2) and the outer shell (objective O3).

The first objective (O1) is to develop a method for information requirements analysis for Business Intelligence systems using System Dynamics. The aim is to improve the information-state with regard to role-specific information requirements of decision makers. In order to distill essential information in a complex and interwoven world (Sterman 2001), the prioritization of measures remains a key challenge for information requirements analysis (Stroh et al. 2011). Since the information requirements are primarily derived from a potential demand of the user, the method can be allocated to the group of demand-driven approaches for information requirements analysis (Strauch 2002).

The second objective (O2) is to demonstrate the applicability of the developed method. Since the method requires the role-specific decision field to be captured in a System Dynamics model, the method – coined I²RDM – is applied to three different System Dynamics models developed for different purposes in different problem domains. Hence, the following sub objectives can be distinguished:

- The first sub objective (O2a) is to develop a System Dynamics optimization model. The proposed simulation-based decision support model aims at determining the optimal payment amount for a complaint solution in the service industry considering fundamental relationships.
- The second sub objective (O2b) is to develop a System Dynamics explanation model. The proposed model aims at combining existing scientific findings to an integrated model to explain the economic implications of word-of-mouth effects considering causal interdependencies.
- The third sub objective (O2c) is to develop a System Dynamics forecast model. The proposed model aims at externalizing and socializing diffused knowledge on non-renewable resources within a company in order to forecast the price development of this non-renewable resource.
- Finally, the fourth sub objective (O2d) is to evaluate the proposed method for information requirements analysis for Business Intelligence systems (I²RDM). It is orthogonal to the first three sub objectives in the sense that each System Dynamics model is used as a case to which the I²RDM method is applied.

The third objective (O3) is to leverage the existing information supply of Business Intelligence systems in a systematic and IT-supported manner. The aim is to improve the information-state of decision makers with regard to user-individual information requirements. The proposed extension for information requirements analysis methods utilizes the existing “data treasure” in companies. Thus, it can be allocated to the group of supply-driven approaches for information requirements analysis (Strauch 2002).

Figure 1-3 visualizes and summarizes the objectives and their purpose.

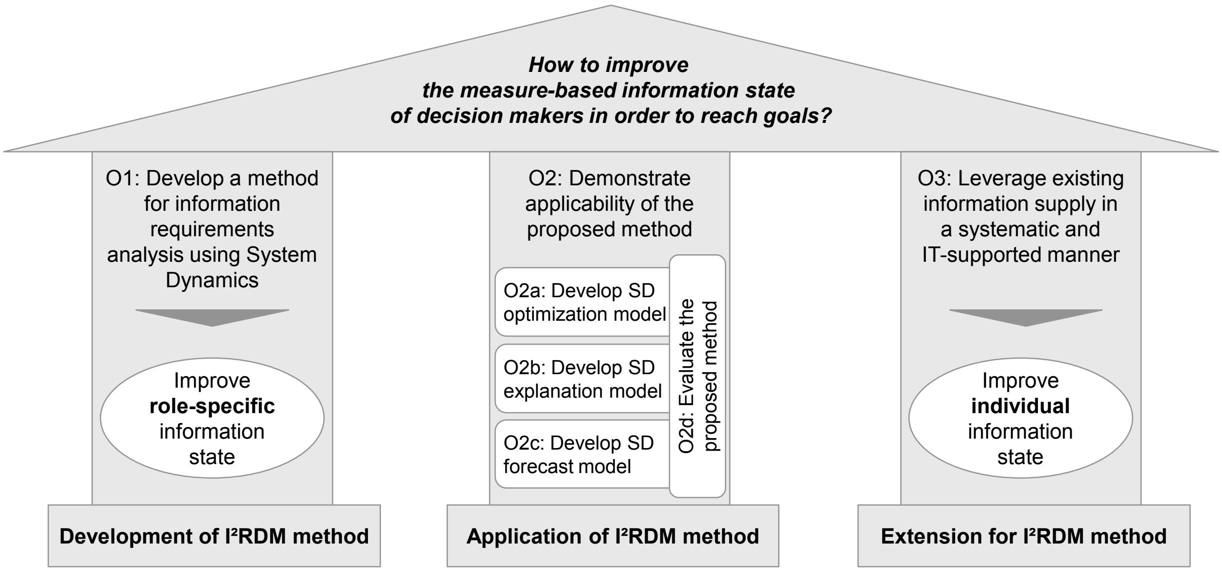

Figure 1-3: Research question and objectives

1.4 Structure

The structure of this dissertation (see Figure 1-4) reflects the objectives depicted in Figure 1-3 and consists of three major parts. First, the demand-driven I²RDM method using System Dynamics for information requirements analysis is developed (chapter 2). Second, the method is applied to three existing System Dynamics models (chapter 3). Third, a supply-driven extension for information requirements analysis methods is proposed that relies on the usage of metadata (chapter 4). Finally, the conclusion summarizes key findings and points out further research need (chapter 5).

Chapter 2 proposes the I²RDM method for the identification and prioritization of information requirements of decision makers using System Dynamics. It starts with a description of the problem setting in section 2.1. Section 2.2 frames the issue by stating the research need from literature and provides required scientific background. Section 2.3 proposes and discusses a procedure model as central artifact of the I²RDM method. The method is evaluated against method design principles in section 2.4. Finally, section 2.5 summarizes the results and reflects on limitations of the I²RDM method.

The method's feasibility is demonstrated in chapter 3 based on three different System Dynamics models. These three cases are presented in sections 3.1, 3.2 and 3.3. Each section is structured identically. First, the business demand for that specific System Dynamics model is distilled. Second, necessary theoretical background of the problem context and related work is provided. Third, the System Dynamics model is developed. Its description contains both model structure and model behavior. Furthermore, the model is simulated using scenarios and limitations are critically reflected. Fourth, the proposed I²RDM method is applied to the model. The chapter ends with the summary of insights from the method's application to the three cases (section 3.4).

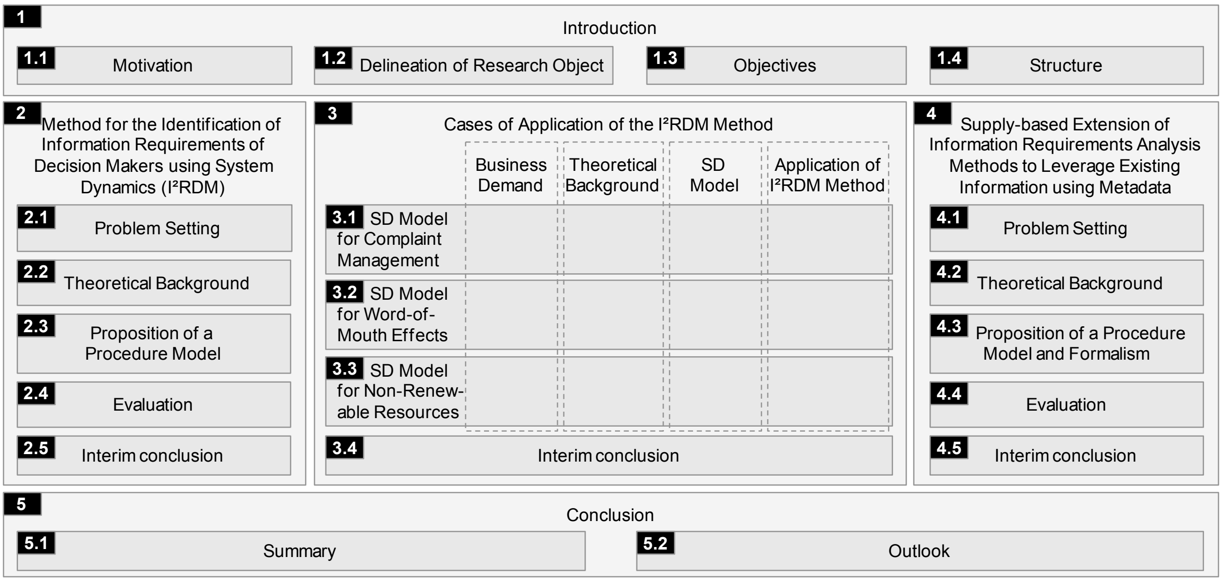

Figure 1-4: Structure of dissertation

Chapter 4 complements the presented demand-driven I²RDM method by a supply-driven extension to leverage the existing information base. Section 4.1 describes the problem setting. Section 4.2 provides necessary theoretical background before the extension – a concept consisting of a procedure model and corresponding formalism – is proposed in section 4.3. As evaluation, a demonstration example is introduced in section 4.4. Section 4.5 summarizes the results and discusses limitations of the extension.

The dissertation concludes with a summary of the overall results (section 5.1) and an outlook on possible further research (section 5.2).

2 Method for Identifying Information Requirements of Decision Makers Using System Dynamics (I²RDM)[2]

Despite valuable related work, identifying relevant information requirements of decision makers is still a key issue in developing Business Intelligence systems. Since measures build a major basis for managerial decision making, discovering the objectively most important measures is crucial to reduce information overload and improve decision quality. Therefore, the I²RDM method is proposed to help decision makers to identify and to prioritize their role-specific measure-based information requirements using the System Dynamics methodology. As a result, objectively needed and subjectively believed to be needed information requirements are aligned.

By relying on method engineering and a deductive approach, this chapter outlines a method to identify and prioritize a decision maker's measure-based information needs thereby improving the alignment of objective and subjective information requirements. It is structured as follows. Section 2.2 frames the issue by stating the research need from literature and provides required scientific background. Section 2.3 proposes and discusses a procedure model as central artifact of the I²RDM method. The method is evaluated against method design principles in section 2.4. Finally, section 2.5 summarizes the results and reflects on limitations of the I²RDM method.

2.1 Problem Setting

As March and Hevner (2007) point out, “IS professionals [have a] lack of adequate methodology to determine executive information needs” (p. 1035). Euler et al. (2010) also identify the need for an improvement of analyzing capabilities – especially since careful a priori analyses of informational requirements constitute a success factor. Subsequently, System Dynamics as methodological basis is used to fill this gap. This approach seems promising since structural (cause-and-effect relationships) and behavioral (equation-based simulation) aspects can be combined. While other approaches are also able to comprehensively express causal relationships (such as Balanced Scorecards or Strategy Maps (Strecker et al. 2012)), they lack the quantitative ties between these relationships required to prioritize information requirements. Approaches focusing, for instance, on correlations (Röglinger 2009) consider these

2 Chapter 2 is, except for marginal changes in details, identical with Mosig (2012), a paper written by the author of this dissertation and published in the Proceedings of the 45th Hawaii International Conference on System Sciences.

ties but lack the causal connections between information structures. Hence, the possibility to combine qualitative descriptions with quantitative simulations is a vital advantage of System Dynamics.

The proposed method focuses on the alignment of objective and subjective information requirements (see Figure 1-1) as a specific aspect when designing Business Intelligence systems. Admittedly, the question as to what qualifies as “objective” information requirements is difficult to answer. With the exception of legally mandatory information, the question of objectivity is rather philosophical. Hence, subsequently objective information requirements are understood as all information that is actually relevant to fulfill a decision maker’s respective tasks in accordance with the company’s objectives. Subjective information requirements in contrast are that information he or she believes to need.

2.2 Theoretical Background

As mentioned before, methods for information requirements analysis are usually categorized into supply- or data-driven and demand- or requirement-driven approaches. Since the first rely on the reengineering of data schemas of transactional information systems, they risk stimulating information proliferation and waste resources due to unneeded information structures (Winter and Strauch 2003). On the other hand, demand-driven approaches start with informational requirements of decision makers – with the disadvantage that decision makers often struggle to specify their information needs exhaustively and unambiguously. To address this issue, various approaches as the analysis of business processes, the use of so-called business questions or techniques as task or document analysis, interviews and surveys (and combinations) have been suggested in literature (Winter and Strauch 2003). For a detailed overview of various approaches see Stroh et al. (2011).

This recently published state-of-the-art article on information requirements analysis also serves as basis to distill the need for action and derive those prerequisites that should be fulfilled by the I²RDM method supporting decision makers to (better) recognize their objective information requirements with regard to measures. Since one identified prerequisite of Stroh et al. (2011) is method support, essential elements for methods are introduced. Finally, related work using System Dynamics in general and performance measurement in specific is presented to provide the foundations for the procedure model proposed in section 2.3.

2.2.1 Information Requirements Analysis

Stroh et al. (2011) provide an extensive state-of-the-art literature review covering publications dealing with information requirements analysis for analytical information systems from 1991 to 2009. Based on an examination of 97 English- and German-language articles they identify – amongst others – following five main improvement needs.

1. **Prioritization (N1).** While many publications derive information requirements from goal formulations, it remains unclear how information requirements should be prioritized. Taking into account the described information proliferation, there is a strong need for action which has already stimulated many scientific contributions seeking for the right tradeoff between information overload and undersupply (see e.g., Röglinger 2009).
2. **Validation (N2).** The validation of information requirements with business users is rarely addressed – and if only by interviews. Stroh et al. (2011) suggest a more formal specification and validation using prototyping.
3. **Documentation (N3).** A comprehensive but intuitively understandable documentation of information requirements is required, as Stroh et al. (2011) point out: "In practice, there is a strong need for models and documentations that can easily be understood by business and IT, without, however, losing precision in the specifications" (p. 40).
4. **Process perspective (N4).** Due to constantly changing company environments and the resulting evolutionary character of Business Intelligence systems, a continuous identification, derivation and management of information requirements is necessary.
5. **Method support (N5).** While many existing approaches show characteristics of a method, they do not provide the required level of detail and remain too generic.

2.2.2 Method Engineering

Since method support has been identified as one of the areas in need for improvement (N5), subsequently prerequisites of method engineering are presented that will serve as evaluation framework in section 2.4.

Based on a literature review, Braun et al. (2005) state that the appropriate construction of methods is an important scientific topic within the design science approach. The "use of methods constitutes the basis for [an] engineering-based procedure" (p. 1296) and is characterized by four fundamental attributes: goal orientation, systematic approach, principles, and repeatability. Furthermore, they identify six fundamental elements a method description requires (specification document, meta model, role, technique, procedure model, and tool) and show that literature-based deduction – as chosen in this chapter – is a feasible research method for method engineering.

Offermann et al. (2010) extend this and other previous work aiming at increasing the utility of method design artifacts through a better comparability of its elements. They distinguish the following eight elements: ❶ **Purpose and scope** (statements about the kind of output, the characteristics of that output, and the characteristics of the method itself), ❷ **Constructs** (terms that need to be introduced, e.g. using a meta model to describe the building blocks of the method, possible interrelationships, and rules for connecting them), ❸ **Principles of form and function** (description of the method following the chosen meta model), ❹ **Artifact mutability** (the degree to which changes in the method itself or an instantiation of a method are foreseen), ❺ **Testable propositions** (that refer to either “truth” or “utility” of a method whereby a design-oriented approach should primarily focus on the “utility” with respect to the purpose), ❻ **Justificatory knowledge** (supporting transferability and validity, e.g. through referencing existing and accepted methods and/or theories), ❼ **Principles of implementation** (meaning to implement a generic method in a specific situation), and ❽ **Expository instantiation** (as e.g. a fictional example of an instantiated method in a specific situation).

This structure is adopted and used as basis for the evaluation of the proposed I²RDM method. Thereby, both later refinements and the possibility to compare the I²RDM with other methods are enabled.

2.2.3 System Dynamics

The I²RDM method heavily draws upon System Dynamics, a methodology able to comprehensively identify, analyze, and simulate complex causal structures of managerial systems. According to Morecroft et al. (1994), the application of System Dynamics models often results in revisions and adaptations of decision rules and learning effects in terms of future decision making. These enhancements are based on the consideration of time delays, nonlinearities, and non-intuitive feedback loops within the methodology (e.g., Sterman 2000; Wolstenholme 2003).

The frequently cited flight simulator metaphor (Sterman 2000) might help to understand the value of System Dynamics models and its fit for information requirements analysis: On the one hand, pilots use simulators to learn more quickly to fly a real aircraft. In general, the use of models enables a faster, cheaper, and safer education. But on the other hand, they also feedback their real-world experiences to improve the flight simulator – which in turn improves future trainings. In general, models also contribute to research: Findings on behavior, especially concerning potentially dangerous exceptional conditions, can be gained to improve the behavior of a system in real world. Practitioners can give further feedback on how to design a model as close to reality as possible.

"Since SD strives for the goal of qualitative description and exploration as well as quantitative simulation and analysis for the design of complex system structure and behavior" (Sterman 2000 cited according to Meier and Reinwald (2010, p. 4)), it can be used as "simulator for decision makers" where measures adopt the role of cockpit instruments. In this sense, a System Dynamics model helps a decision maker to realize his or her "true" information needs regarding measures and to value them appropriately.

There are two vital articles combining issues of performance measurement with System Dynamics. Santos et al. (2002) suggest a combination of System Dynamics and multicriteria analysis to "make [different steps of] the performance measurement and management process more efficient and effective" (p. 1267). Sousa et al. (2005) extend these thoughts and propose a structured engineering approach for conceptual design of enterprise performance measurement systems. Yet the level of detail remains quite abstract, a procedure model is missing, and the link to the company's objectives to derive more objective information requirements is not explicitly demanded.

So while System Dynamics can and has been used to support decision making (Boulanger and Bréchet 2005) and it has been shown that the improvement of mental models of decision makers through System Dynamics models actually increases the quality of managerial decisions (Lyneis and Ford 2007; Senge 1994; Sterman 2010), approaches on how to include the possibilities of System Dynamics in methods for information requirements analysis do not provide sufficient methodical support on how to derive and prioritize measures. This research gap is addressed in the subsequently proposed procedure model.

2.3 Proposition of a Procedure Model

A procedure model is the central element of each method (Braun et al. 2005). Therefore, subsequently a procedure is proposed to derive the importance of measures. Thereby, decision makers can realize what information actually is most relevant (objective information requirements) compared to those information he or she believes to be most relevant (subjective information requirements). The underlying assumption is that through this learning process objective and subjective information requirements get "better" aligned.

2.3.1 Description

Since the suggested method is based on System Dynamics, Sterman's (2000) well-established iterative System Dynamics modeling process has been selected as basis. Compared to other available processes to create System Dynamics models (such as proposed by Abbas and Bell 1994; Barlas 1996; Coyle 1983; Forrester 1994; Pfahl and Lebsanft 1999), his process provides the highest level of detail and outlines various possible validation types in detail. He suggests five stages: problem articulation, formulation of dynamic hypothesis, formulation of a simulation model, testing, and policy design and evaluation. The seven steps of the subsequently proposed method roughly coincide with this structure, whereby Sterman's second stage (formulation of a dynamic hypothesis) is further divided into the three steps B, C and D. Figure 2-1 shows an overview of the proposed procedure model.

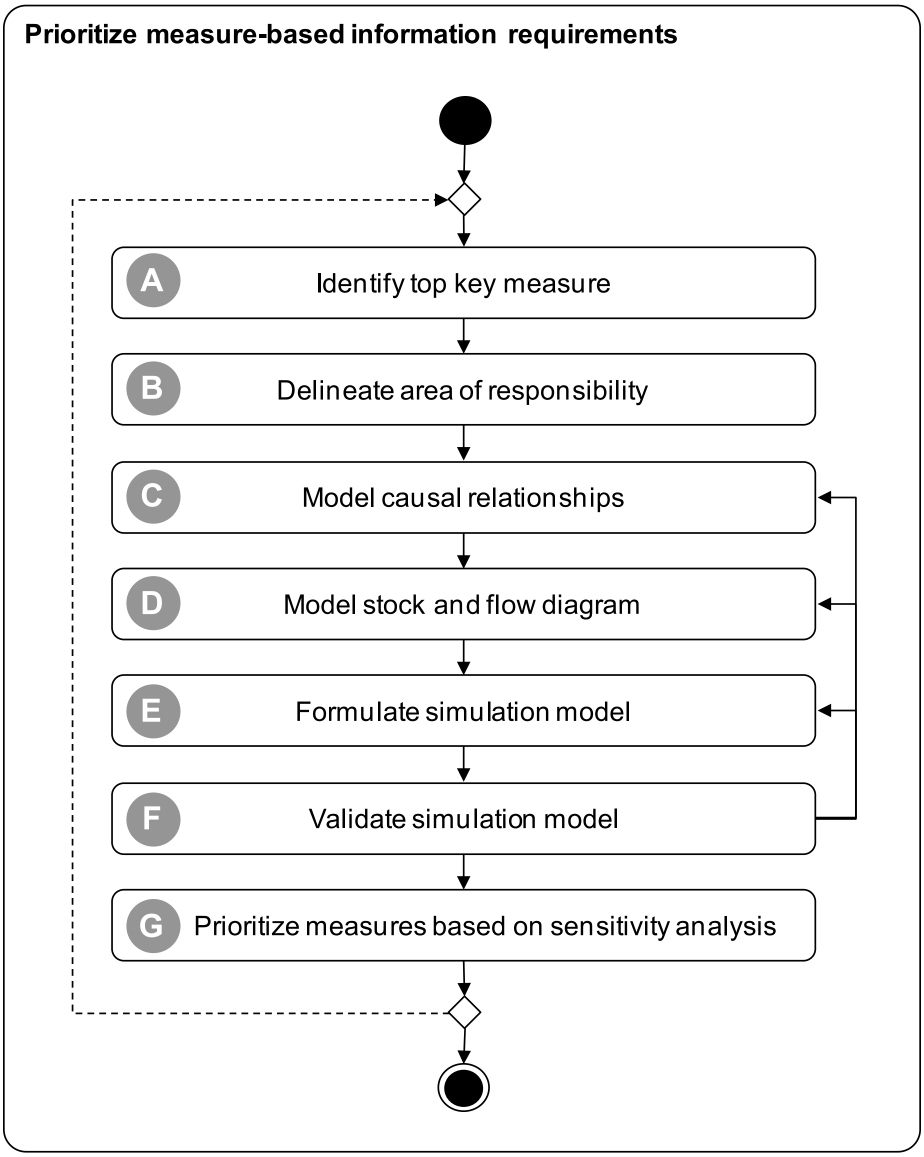

Figure 2-1: Procedure model of the I²RDM method

As a first step (A), the corporate objective system needs to be made explicit. In order to identify the informational requirements (“most important” measures), a decision maker requires to decide in line with a company’s objectives. Hence, the importance of a measure should be defined as the degree to which the measure influences the achievement of a company’s objectives.

Adopting a value-based management view, all objectives must be ultimately linked to one or more financial measures (note that if more than one measure is established, an aggregated top key measure based on a weighting is required). This view seems appropriate since it is generally accepted as theoretical framework in economic research and enables the consistent evaluation of decision effects across functional areas and hierarchies (Coenenberg and Salfeld 2007).

In a second step (B), it is necessary to delineate a decision maker’s area of responsibility and establish its link to the corporate objective system. The purpose of the System Dynamics model is to answer the following two types of questions: (1) To what extent does the variation of one variable (ceteris paribus) affect the top key measure? (2) To what extent does the variation of one variable require a decision maker to take corrective actions? While at first sight both questions seem exchangeable, the answers may be different as one of the examples in chapter 3 will show.

Step B is of utmost importance since model boundaries set too narrowly will result in the exclusion of corresponding information requirements. On the other hand, a scope defined too broadly increases a model’s size and complexity which disproportionately increases modeling effort and detracts attention from the essential underlying relationships. A so-called model boundary chart stating endogenous, exogenous and excluded variables can contribute to inter-subjective comprehensibility of the system’s delineation (Sterman 2000).

The third step (C) comprises the identification and modeling of causal relationships. Empirically observed correlations can serve as starting point to identify causal relationships. The set of all cause-and-effect-relationships between variables form the feedback structure of a system and are documented in a causal loop diagram.

The development of a stock and flow diagram is done in step D. The feedback structure is translated into the underlying physical structures (e.g. flows of material, money or information) (Sterman 2000) consisting of stocks and flows. Stocks are storage elements that can only be increased or decreased by flows. The strength of a flow is always regulated by exactly one valve. Flows connect either two stocks or a stock and a source/drain (i.e., unlimited stocks outside a model’s boundaries). Converters are auxiliary variables that are used to regulate valves or alter other converters. These relationships are depicted by connectors (see Figure 2-2).

In step E, the simulation model is formulated through specification of equations, parameters and initial conditions in the stock and flow diagram. Equations describe the behavior of one variable depending on one or more other variables over time. In this step, it is important to find the right balance between model accuracy and pragmatism. Since the models purpose is to identify the importance of measures based on a sensitivity analysis, it is necessary to start with realistic assumptions regarding parameters and initial conditions.

The sixth step (F) comprises the validation of the model. Different concepts and methods have been proposed for formal System Dynamics model validation. While validation of a model must also include semi-formal and subjective parts (e.g. in order to validate the fit to its purpose), the sixth step of the proposed method follows Barlas (1996) argumentation and focuses on formal aspects of model validity but does not include philosophical aspects (while not neglecting them). Both structure (direct structure and structure-oriented behavior tests) and behavior (behavior pattern tests) validity can be tested. A direct structure test focuses on the formal soundness (e.g., a dimensional consistency test checks if dimensions on the left-hand side of an equation match the right-hand side). Structure-oriented behavior tests try to uncover structural flaws by wrong behavior (e.g., the application of extreme values causes an improper model behavior). Behavior pattern tests have been suggested to check if long-term patterns produced by the model match the observed reality. An extensive overview of possible tests has been presented by Barlas (1996).

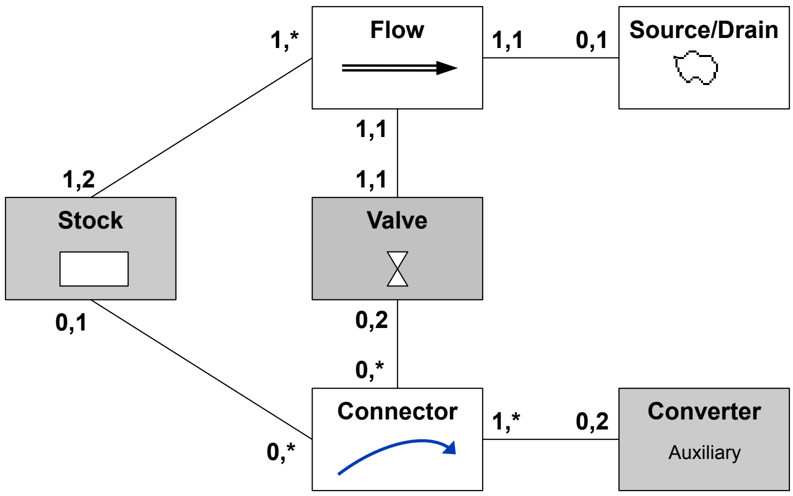

Figure 2-2: Meta model for stock and flow diagrams

The prioritization of measures is the last step (G). Figure 2-2 shows the meta model for stock and flow diagrams (as described in step D) following the notation for meta models suggested by Ferstl and Sinz (2008). Stock, valve and converter (sometimes also called auxiliary variable) elements are interpreted as potential measures (dyed grey) required by a decision maker.

For these elements, a sensitivity analysis is made. The goal is to identify the influence of (ceteris paribus) variations of one measure on the top key measure – considering the modeled time delays, feedback loops and nonlinearities. An isolated view based on simpler estimations (as e.g., rule of proportion) cannot reproduce these effects. Note that only an analysis of numerical sensitivity is conducted (meaning that a change in assumptions alters the numerical values of other variables (Sterman 2000)) and behavior mode or policy sensitivity are not considered.

While the sensitivity analysis reveals the importance of a single measure with regard to its influence on the top key measure, the difficulty to obtain the measure is not yet considered. While one could argue that this is not part of information requirements analysis, in a real-world setting decision makers might favor measures that can be made available in a timely manner and at no extra cost. In literature, prioritization approaches considering, for example, cost, implementation time, data quality and other aspects can be found in different combinations (Winter and Strauch 2003). In order to aggregate these considerations, a single dimension called availability is introduced (a low availability would indicate that a high investment is required to automatically collect a measure or that manual work is required).

Figure 2-3 shows a 3x3 matrix integrating the two dimensions importance and availability. Based on an individual weighting a prioritized order of the measures can be established. In this case, measures would be sorted into three classes (indicated by different shades of grey – with darker shades indicating a higher prioritization). Companies may change this prioritization, for example, in order to over-proportionally value importance over availability or to define a higher granularity of classes.

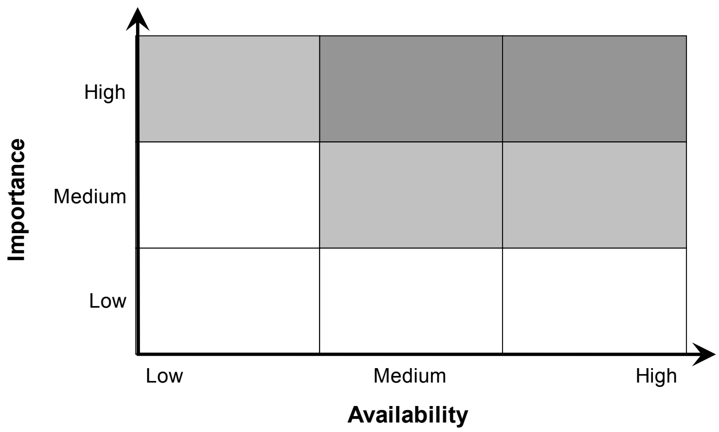

Figure 2-3: Prioritization matrix for measures

2.3.2 Discussion

This section discusses advantages and disadvantages of the proposed procedure model with regards to the identified improvement needs for information requirements analysis.

Admittedly, the proposed procedure model involves a lot of manual effort and interaction between decision makers and analysts. Even if a suitable System Dynamics model is available as starting point, model boundaries and the link to corporate objectives need to be established or confirmed, initial values for an instantiation of the equations are required and the results have to be iteratively discussed triggering new adaptations of the simulation model. On the other hand, all five described improvement needs can (at least partially) be addressed:

1. **Prioritization (N1).** The proposed procedure leads to a quantitative prioritization of all modeled measures. A numerical sensitivity analysis reveals a measure's influence on the top key measure. This demand-based prioritization is supplemented by a supply-based qualitative prioritization that has not been further detailed so it can be adapted to consider company-specific preferences (e.g., higher valuation of cost aspects compared to data quality). An extension – that will be proposed in chapter 4 – offers another possibility to utilize the existing information supply and might be linked to the availability dimension.
2. **Validation (N2).** While the resulting artifacts as causal loop diagrams, stock and flow diagrams and simulation results cannot be seen as a prototype in its traditional sense, they show both structure and behavior of the interconnectedness of measures and hence build a kind of "informational prototype". A use of these artifacts in interviews may help to validate information requirements in a semi-formal way.
3. **Documentation (N3).** The generated System Dynamics artifacts also fulfill documentary purposes: They are comprehensible without a mathematical or IT education and have been used for discussions with decision makers (Lyneis and Ford 2007).
4. **Process perspective (N4).** This need does not refer to the iterations in the proposed procedure model but to a regular review of a decision maker's information requirements (indicated by the dotted line in Figure 2-1). Since all required artifacts are already available and only changes have to be incorporated, the effort will be significantly reduced.
5. **Method support (N5).** While a procedure model is an important part of any method, other elements need to be considered as well. Hence, the next section examines what is missing to claim "full" method support.

2.4 Evaluation

In this section, the eight elements Offermann et al. (2010) suggested for evaluation are used to discuss the potential to extend the presented procedure model to a comprehensive method.

❶ **Purpose and scope.** The method aims at facilitating the alignment of objective and subjective information requirements in order to identify the "right" measures a decision maker needs to be aware of. It should be applied when decision makers suffer from information overload and struggle to appropriately value the importance of individual measures. Potential users are all actors involved during information requirements analysis, especially decision makers and business analysts.

The primary result is a list of prioritized measures that takes into account both importance and availability of a measure. A side output is the continual learning of involved decision makers about cause-and-effect relationships and interrelations thereby transparently revealing underlying assumptions that can ultimately also improve decision quality (Lyneis and Ford 2007; Senge 1994; Sterman 2010).

❷ **Constructs.** Constructs can refer to the method itself, its output or the enactment context (Offermann et al. 2010). While a meta-model for stock-and-flow diagrams following the System Dynamics methodology has been introduced and linked to measures, other terms and constructs (as, e.g., a meta-model for the steps in the procedure model) have not been described due to its intuitive comprehensibility. Hence, a proper documentation of all constructs (that would go beyond the scope of this dissertation) is missing for a “full” method.

❸ **Principles of form and function.** This part coincides with section 2.3 which describes the procedure model as core element of any method. Again, the level of detail could be elaborated. For example, it remains unclear what roles have to interact how in order to derive the results for each step of the procedure model.

❹ **Artifact mutability.** Changes to the method itself are not foreseen since all proposed steps are necessary. Leaving out a step would result in measures endangered of no reference to corporate objectives (in case of excluding step A), a model size no longer feasible (if step B is omitted), lower result quality (if leaving out step F), or no results at all (in case of excluding step D, E or G).

On the other hand, artifact mutability also refers to changes in the instantiation of a method (Offermann et al. 2010). Within the steps, variations are possible. While there is a need for a system of objectives, this has not necessarily to follow a value-based management approach (step A). Another example refers to step G. The final prioritization of measures can be altered in any favored way – reaching from a pure emphasis on information demand to a very high consideration of different aspects of information supply (as, e.g., cost or data quality).

❺ **Testable propositions.** Since “a method is valid if it is useful in respect to the purpose” (Offermann et al. 2010, p. 300), a practical application still has to show that the method actually fosters a better alignment of subjective and objective information requirements and improves the role-specific information state of a decision maker. Even if the proposed steps are based on previous scientific results, match the existing body of knowledge and are convincing in its deductive logic, a real-world proof is missing.

Two scenarios can be distinguished to prove the utility. In the less severe one, the appraisal of decision makers would be sufficient. A possible setting would be to ask a representative group of decision makers with the same area of responsibility for a fix number of most important measures, run them through the procedure model and repeat the question. If the selected measures change and if the decision makers believe the new set would help to make better decisions in line with corporate objectives, the utility of the method would be assumed.

In the more severe scenario, a higher coverage of objective information requirements would need to be linked to a higher achievement of a company’s objectives. This results from the previously introduced understanding of objectivity, referring to an improved information base to fulfill all tasks in accordance with the company's objectives. However, it remains questionable if a resilient link to utility of the method can be established because side effects (as, e.g., variations in decision quality) are very difficult to exclude.

❻ **Justificatory knowledge.** The proposed method heavily draws upon previous work in System Dynamics. The System Dynamics methodology has existed for more than 40 years, has been successfully applied to various contexts (including but not limited to decision support in business environments) and reached a level of maturity where many models are already available and can serve as starting point (three examples will be presented in chapter 3). While it has often been criticized that model outcomes only reflect assumptions, the usefulness of models to influence and improve the so-called mental model of decision makers has been confirmed (Sterman 2000, 2010). The issue of model validity has also been extensively examined (Barlas 1989, 1996).

Transferring und utilizing the System Dynamics methodology to improve information requirements analysis in the suggested way seems especially promising since humans tend to underestimate dynamic and non-intuitive behavior caused by delays, feedback loops and non-linearities (Sterman 2010).

❼ **Principles of implementation.** When the suggested method is implemented, iterations will be necessary to properly define the model's boundaries, identify variables and their relationships and create the simulation model. Furthermore, involvement of both decision makers and business analysts is required. The first have deep knowledge on the business context, the latter contribute the technical and methodical skills to translate this knowledge into the required models.

But while iteration and joint modeling are two principles of implementation, other principles are subject to further research. For instance, these could give additional advice on how to adapt the proposed I²RDM method in a specific situation.

❽ **Expository instantiation.** Both the (fictional) derivation for a particular context and situation or a report on real-world execution of the method are possible instantiations (Offermann et al. 2010). Hence, chapter 3 demonstrates the methods application for three different cases.

In summary, the main points missing to claim a “full” method are an extensive documentation including definitions of all terms and meta models, a proof of utility in a real-world setting, and further principles providing advice when implementing the method. Otherwise, no road blocks have been identified. Further research might address the issues thereby developing further the proposed I²RDM method.

2.5 Interim Conclusion

In this chapter, the I²RDM method was developed to improve information requirements analysis for Business Intelligence systems by using System Dynamics to identify and prioritize role-specific and measure-based information requirements of decision makers. The presented procedure model drawing from the System Dynamics methodology can help to overcome current shortcomings in information requirements analysis such as, for instance, missing prioritization. The method was evaluated referring to method engineering research and ideas for further development were suggested. An extensive documentation of terms and meta models, a proof of utility in a real-world setting, and further implementation principles are beyond the scope of this dissertation and, thus, leave room for further improvements.

Admittedly, the suggested I²RDM method entails some limitations that need to be critically considered:

- First, the effort required to create the System Dynamic models and equations for a subsequent prioritization is very high. In comparison with other requirements engineering approaches it is probably too high if only their value for information requirements analysis is considered. But if existing System Dynamics models for decision support are used as starting point (as will be shown in chapter 3) and if initially built models can be reused in similar areas, a cost/benefit consideration can (despite the high complexity) result in a positive result.

- Secondly, the problem domain is limited to rather operational and repetitive decisions that rely on measures. While this category constitutes a significant share of decisions, other approaches for information requirements analysis (as, e.g., the use of business questions) do not face this limitation. Then again, the suggested System Dynamics-based simulation enables a comprehensible prioritization of measures based on a company's objectives that cannot be derived by existing approaches.
- Thirdly, each model necessarily is an abstraction and therefore simplification of the real-world. Its output quality heavily depends on the input quality. Hence, results need to be carefully checked with respect to its fit for the intended purpose.

But despite these limitations, the proposed I²RDM method utilizes the potential of System Dynamics to contribute to information requirements analysis by aligning objectively required and subjectively believed to be required, role-specific and measure-based information requirements of decision makers.

3 Cases of Application of the I²RDM Method

This chapter addresses the first limitation of the proposed I²RDM method, namely the high effort required to create System Dynamics models, and examines how existing System Dynamic models that have been developed for different purposes in different problem domains and contexts, can be used as input for the proposed I²RDM method. Table 3-1 shows the different kinds of the models, their problem domains and the purpose of the respective models.

Table 3-1: Overview of the three cases

#	Kind of Model	Problem domain	Purpose
1	Optimization model	Complaint management	Decision support
2	Explanation model	Word-of-mouth effects	Simulation of interdependencies
3	Forecast model	Non-renewable resources	Knowledge management

Subsequently, the three models are presented. At first, the business demand for that specific System Dynamics model is distilled. Second, necessary theoretical background of the problem context and related work are provided. Third, the System Dynamics model is developed. Its description contains both model structure and model behavior. Furthermore, the model is simulated using scenarios and limitations are critically reflected. Fourth, the I²RDM method proposed in chapter 2 is applied to the respective System Dynamics model. The chapter closes with an interim conclusion (section 3.4) that summarizes insights from the method's application in the three cases.

3.1 System Dynamics Model for Complaint Management[3]

The subject of this section is a dynamic simulation model that helps to determine the optimum amount of payment in terms of value-based management for a complaint solution in the service sector. Thereby, the central point is the conflict between the loss in value due to defecting customers on the one hand and the loss in value due to exaggerated investments in customer loyalty on the other. Simulation results show

[3] Sections 3.1.1 to 3.1.3 were written in collaboration with the supervisor of my dissertation, Prof. Dr. Marco C. Meier, and Dr. Dieter Reinwald (FIM Research Center) and are, except for marginal changes in details, a translation of Meier et al. (2011).

that previous approaches do not sufficiently consider decisive factors. The model is evaluated based on an example from the mobile telecommunication industry. Thus, the model provides new insights for the development of decision support systems.

3.1.1 Business Demand

Complaint management as integral part of a CRM (customer relationship management) system is still widely neglected, despite its high potential to contribute to the increase of shareholder value – and thereby to a primary goal of information systems research (Mertens 1999).

This is backed by studies (Bitran and Mondschein 1997, Mittal and Kamakura 2001) that claim it causes in some cases five times more effort to win a new customer than to keep a dissatisfied customer through a purposeful complaint management. The problem is that these findings are presented comparatively undifferentiated. The value contribution of a specific measure aiming at keeping a customer may depend on a number of factors (Fornell and Wernerfelt 1987, Stauss and Seidel 2007).

In practice, decisions are made on such “defensive measures” without knowing to what extent they contribute to increasing shareholder value or avoiding loss of value (Bain et al. 2002). In some cases, a rational is completely lacking, so that the treatment of a complaining customer (complainant), for example in a call center, depends arbitrarily on the randomly assigned employee. In other cases, there are simple flat-rate policies that determine that a failure of a particular category always implies the payment of a fixed amount as a complaint solution, for instance, in form of a voucher. In slightly more advanced (analytical) CRM systems, the decision about how much is invested in a customer who is prone to leave, is based on simple metrics, such as the sales of recent years, or simple methods for customer prioritization, such as one-dimensional ABC- or multi-dimensional RFM (recency-frequency-monetary value) analyses. However, all these approaches focus on the past and their contribution to the shareholder value is opaque. Thus, they bear the risk of a wrong decision in terms a value-oriented management (Baker and Collier 2005).

A value- and future-oriented measure for prioritization is the Customer Lifetime Value (CLV), that is, the discounted value of the difference between all cash inflows and cash outflows that a customer will create. Because of the problem of assigning especially larger cash outflows, as for instance salaries of employees, to a single customer, it makes sense to use the sum of the CLVs of all customers of a homogeneous segment instead of their individual values. The so-called Customer Equity can be used here as measure for the value contribution of a CRM measure (Heidemann et al. 2009).

In practice, these measures are often missing in standard reporting (Heidemann et al. 2009), although data warehouses or data marts would contain the required data for calculation, stemming from both internal sources (such as enterprise resource planning systems) and external sources (such as market research institutes and statistical offices). The potential to use these data for value-oriented decision making is not fully exploited for a number of reasons: short-term objectives dominate, there is a lack of methodological knowledge and/ or technical skills, etc.

First scientific articles already deal with approaches for value-oriented decision support systems for complaint management, but these are in some aspects too undifferentiated since they do not , for example, take into account long-term feedback effects (Baker and Collier 2005). In addition, they have not yet reached the real world on a larger scale because many companies – as outlined above – do not yet have the required measures available.

Hence, there is a need to improve decision support systems for complaint management regarding their future and value orientation, the consideration of both short- and long-term effects, as well as the inclusion of feedback effects.

Definition of Research Object

Object of research are information systems that help to prepare complaint management decisions. Assuming a given customer base – the acquisition of new customers through “door opener” that may result from an effective complaint management is not addressed in this model – the primary objective of complaint management is the avoidance of opportunity costs caused by lost customers. In other words, future cash inflows at risks of existing customers have to be secured.

Especially in the service sector, which in Germany has reached a share of around 70% of the gross value added (Bundesregierung 2008), there are good starting points for a purposeful complaint management. These result from the contact to the so-called external factor, that is, the customer or an object that belongs to the customer, especially if compared to an anonymous industrial product.

In order to distill cause-and-effect relationships, the model abstracts from other objectives of complaint management, such as the collection of suggestions for the improvement of services. The focus of the model is on one of the key issues in complaint management: How much should the value of the complaint solution for a customer be?

In this context, complaint solution refers to a measure, such as a bonus payment or a special offer (e.g., “Upgrade”), that intends to satisfy a complainant’s expectations so he or she is pleased and continues buying at this company instead of defecting to a competitor.

The expectations of a customer regarding a company's reaction on a perceived deficit could be based on ex ante explicitly formulated "marketing promises", as they occur in so-called service guarantees (Baker and Collier 2005), or emerge implicitly from the nature of a service, the company's reputation, etc. (Kano et al. 1984).

Requirements for a Contribution

Generally, there are four well-accepted basic requirements on contributions in the area of information systems: (1) it should be applicable to a class of problems, (2) it should make an innovative contribution on the published knowledge base, (3) it should be comprehensibly justified and able to be validated, and (4) it should be able to generate a benefit for its stakeholders – either today or in future (Österle et al. 2010).

In the specific problem context of this paper, three additional requirements need to be considered: (A) there should be a monetary result for the complaint solution that (b) is in line with value-oriented management in a transparent way, and (C) takes into account dynamic (feedback) effects.

Ad (A): As previously motivated, the model focuses on decisions for complaint solutions. The scope is given through a value for the complaint solution. That is the reason why this model intends to give a monetary result, in the sense of a "budget" of an "optimal" complaint solution. The decision on a particular type of measure is not within its scope.

Ad (B): The aforementioned "optimality" refers to the contribution of a complaint solution towards the company goal of sustainable shareholder value creation. For the company value in the context of complaint management, the already motivated Customer Equity is a feasible measure. It can be defined as aggregated CLVs (see Gupta and Lehmann 2003, Kumar and George 2007):

$$CE = \sum_{i=1}^{n} CLV_i \,, \qquad with\ CLV_i = \sum_{t=1}^{T} \frac{E_{i,t} - A_{i,t}}{(1+z)^t} \tag{1}$$

with

CE	Customer Equity
CLV_i	Customer Lifetime Value of customer i
n	total number of customers
$E_{i,t}$	expected cash inflows of customer i at time t
$A_{i,t}$	expected cash outflows of customer i at time t
z	required rate of return
T	estimated duration of remaining business relationship

Thus, the central point is the conflict between short-term cash outflows and the potential loss of long-term cash inflows. It is assumed that each complaint destroys a part of the Customer Equity – either due to payments for a complaint solution and/or due to the loss of an existing customer. The case that an experienced sales person might be able to generate additional revenues from a complainant (e.g., due to cross- or up-selling) is not considered. In essence, this means: If the payment for a complaint solution is too small, the customers defects to a competitor and untapped potential customer value – and hence Customer Equity – is lost. If the payment for a complaint solution is too high, the potential loss of future revenues is precluded but at an "excessive" price – and again Customer Equity is lost. Therefore, it is necessary to determine exactly that amount payable at which the loss in Customer Equity is lowest, and, at the same time, the marginal return is still positive.

Ad (C): Since value-oriented management aims at sustainable value creation, analyses for decision support have to take into account long-term effects. This includes time delays, non-linear effects and feedback effects. For example, one might assume that an increasing number of customers also implies an increasing number of complainants. This is caused by the increasing risk of failures due to an increasing number of services. If expectations of complainants are not satisfied, the number of customers will be lower in the next period. This in turn leads to a decrease in the number of complainants. The impact of such delayed reactions on a decision parameter itself is explicitly taken into account in the model.

3.1.2 Theoretical Background

To ensure that the model contributes to the published knowledge base in an innovative way, first it was searched for literature that promises a contribution fulfilling the above described requirements. Two extensive so-called state-of-the-art papers by Homburg and Fürst (2007) and Hogreve and Gremler (2009) serve as starting point. Their work covers both the German and English research literature of the last decades in the areas of complaint management and service guarantees and points out research gaps. In addition, recent publications in journals or conference proceedings that are missing in the above mentioned papers and books and dissertations were searched for and included.

Table 3-2 summarizes the identified relevant papers and books regarding their fulfillment of the postulated requirements.

Table 3-2: Overview of previous research approaches

	Approach	Requirement A Monetary result	Requirement B Value orientation	Requirement C Dynamic effects
Journal or conference paper	Fornell and Wernerfelt (1987)	Quantitative model	Implicitly considered	Not considered
	Hart (1988)	Not considered	Implicitly considered	Not considered
	Reichheld and Sasser (1990)	Not considered	Implicitly considered	Empirical positive correlation between shareholder value and duration of the customer relationship
	Hart et al. (1990)	Not considered	Implicitly considered	Not considered
	Baker and Collier (2005)	Quantitative model	Customer value as input	Not considered
	Liu et al. (2006)	Not considered	Not considered	Simulation over several periods
	Meier and Reinwald (2010)	Not considered	Optimization of Customer Equity	Simulation over several periods
Book or dissertation	Fürst (2005)	Not considered	Implicitly considered	Not considered
	Stauss and Seidel (2007)	Not considered	Global approach using costs and benefits	Not considered

Fornell and Wernerfelt (1987) create an economic model based on the exit-voice theory (Hirschman 1970) and show how complaint solutions can help to substantially reduce the costs of marketing measures. This implicitly contributes to increasing the shareholder value. Dynamic effects are not taken into account.

Hart (1988) calls for a "significant" monetary complaint solution but lacks offering specific recommendations. Instead he describes some examples of flat-rate complaint solutions for all customers. A value-oriented way of thinking is given since the selected exemplary companies outperform their competitors. Dynamic effects are not taken into account.

Reichheld und Sasser (1990) introduce the concept of differentiation in complaint management research. On the one hand, there is now a distinction between profitable and unprofitable customers; on the other hand, they identify a strong positive correlation between the duration of a customer relationship and the resulting shareholder value of a company. Hence, they give a first indication on the importance of dynamic effects.

Hart et al. (1990) emphasize that compensations up to a certain degree should be paid without questioning. However, they do neither provide specific guidelines on the (monetary) amount of the complaint solution nor consider dynamic effects.

Baker and Collier (2005) are the first to suggest a quantitative model that provides a specific recommendation for the (monetary) amount of a complaint solution. Their formal-deductive analytical model is based on the customer value and quantified based on the "long term discounted lost revenues". The increase of shareholder value is explicitly taken into account since (certain) payments and future (uncertain) revenues are optimized. Dynamic effects are neglected, as the authors note self-critically.

Liu et al. (2006) present a System Dynamics model that examines causal relationships of complaint management in the national telecommunication industry. Although they use an empirical study to evaluate the simulation results, the highly aggregated view of their paper does neither provide a specific monetary complaint solution for a homogeneous customer segment nor integrates the concept of value-orientation.

Meier and Reinwald (2010) develop a dynamic model that deals with the optimal split of a given budget for complaint solutions between two customer segments. However, they come up short on providing a specific monetary result. The Customer Equity is used as key measure. Dynamic effects including feedback are considered – especially regarding word-of-mouth effects.

In his dissertation, Fürst (2005) examines empirically the success factors of complaint management. Although he stresses the importance of a physical complaint solution for complainant's satisfaction (and hence success), he does not provide specific recommendations regarding the monetary amount of the complaint solution. While he motivates the importance of complaint management from a value-oriented point of view, he lacks the inclusion of dynamic effects.

Stauss and Seidel (2007) emphasize the importance of a physical and financial component of a complaint solution for complainant's satisfaction, but just make vague statements that these also should depend on the customer value. Dynamic effects are mentioned, but not considered for the determination of the level of a complaint solution.

Research Design

The above-mentioned research showed that there is no publication that provides decision support for the determination of a monetary amount of a complaint solution in the service sector, considers the shareholder value, and takes into account dynamic effects.

Thus, the central cognitive goal of section 3.1 is to determine the optimal value of a complaint solution in the service sector in order to minimize the loss of Customer Equity. This loss is caused by both defecting customers and payments for offering complaint solutions. Thereby, the motivated dynamic effects have to be taken into account. Furthermore, it is important to identify those factors that have the strongest influence on the result. This is necessary to derive specific recommendations for purposeful actions of decision makers.

According to the categorization of Wilde and Hess (2007), the research method of simulation with the goal of optimizing a system's behavior is a feasible approach (Mattern 1996). Due to the dynamic effects that should be taken into account, the simulation method System Dynamics suggests itself. Based on the system theory, this research approach identifies, analyses, and simulates complex causal structures of economic or other systems (Forrester 1971, 1994). The aim is to improve the decision- and learning-processes of decision makers since they – as any humans – lack the intuitive understanding of causal interdependencies. This is caused by time delays and non-linear relationships between model parameters (Wolstenholme 2003). As a development environment for modeling and simulation, the simulation software Vensim® DSS (version 5.9e) is used. The software provides extensive analysis capabilities that help to perform the suggested optimization and sensitivity analyses.

3.1.3 System Dynamics Model

Subsequently, both model structure and underlying assumptions are described and justified. It follows the simulation based on exemplary parameter instantiations. A sensitivity analysis extends the interpretation of results in order to find evidence to what extent changes of selected model parameters influence the optimal complaint solution and Customer Equity.

3.1.3.1 Model Structure

Figure 3-1 shows the stock and flow diagram of the model using the System Dynamics notation (Sterman 2000). It assumes both a homogeneous customer segment and a periodical revenue model.

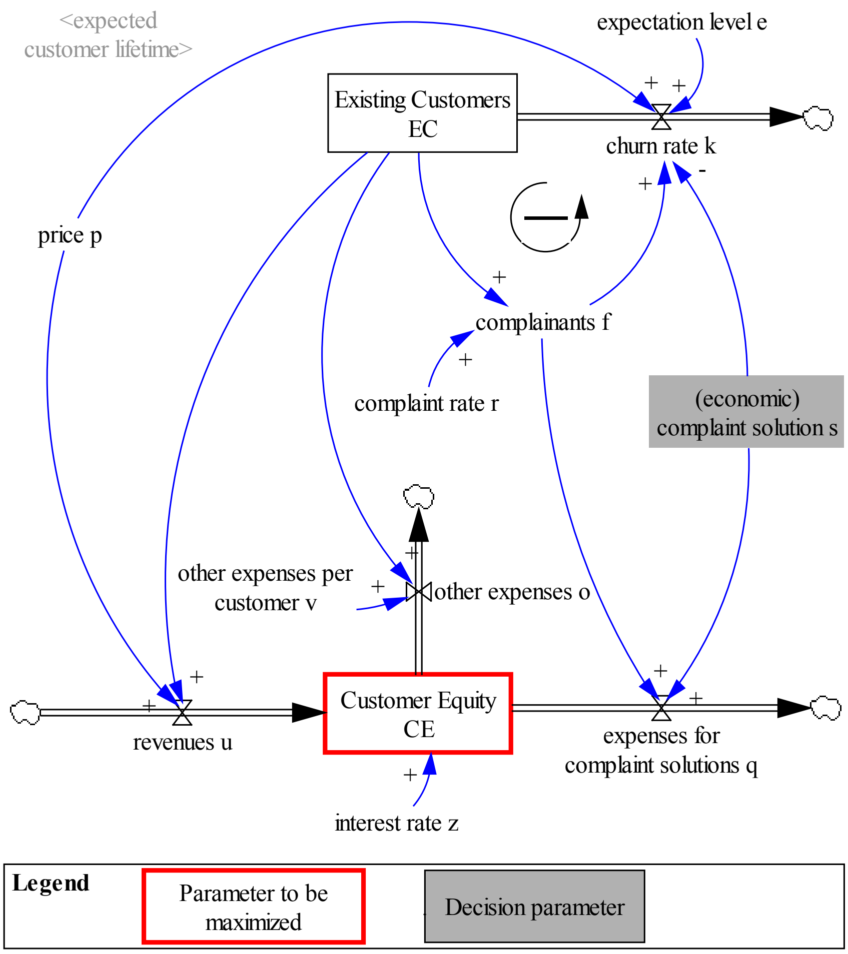

Figure 3-1: Stock and flow diagram of the System Dynamics model for complaint management

The *expected customer lifetime d* ($\in \mathbb{Z}^+$) (depicted as shadow variable) equals the average number of periods a homogeneous customer group will buy the services of a company.

The stock *Existing Customers EC* ($\in \mathbb{N}_0$) contains the number of customers of a homogeneous customer group. In the model, it is exclusively reduced by the flow *churn rate k* ($\in \mathbb{R}_0^+$) per period t. This rate represents that part of the existing customers that defects from the company in period t despite receiving a complaint solution. Thus, the customer base is reduced compared to the previous period (t – 1). Equation (2) describes this relationship.

$$EC(t) = EC(t-1) - k(t) \tag{2}$$

At this point it should be noted that many other influencing factors in customer relationship management might be responsible for the change in the number of existing customers (e.g., reduction of existing customers due to negative word-of-mouth). The direct or indirect influence of these other factors on the number of customers is not considered in this model.

As can be seen from equation (3), the flow churn rate is calculated based on the parameters *complainants f*, *complaint solution s*, *price p*, and *expectation level e* that are explained in the following.

$$k(t) = f(t) * \left(1 - \left(\frac{s(t)}{p(t)}\right)\right)^{e(t)} \tag{3}$$

The variable *complainants f* ($\in \mathbb{R}_0^+$) results from a multiplication of the existing customers and the *complaint rate r* ($\in$ [0, 1]) and represents that share of existing customers that voices a complaint during one simulation period at the company. The higher the complaint rate, the higher the number of complainants per period t. This shows equation (4).

$$f(t) = EC(t) * r(t) \tag{4}$$

Complaints not reaching the responsible department within the company are not within the focus of the model and, therefore, not taken into account. We assume that each dissatisfied customer actually voices his or her dissatisfaction and that this complaint is also registered. Further information regarding the identification of dissatisfied customers can be found – amongst others – in Stauss and Seidel (2008).

The expenses for the complaint solution, the price and the expectations of a customer group (represented by the expectation level) are critical for the model since they influence the probability of repeat purchases in case of complaints.

The decision maker in a complaint management department defines the monetary amount of a *complaint solution s* ($\in \mathbb{R}_0^+$). Thereby, he influences the churn rate: The higher the complaint solution relative to the *price p* ($\in \mathbb{R}^+$) of the service (i.e., the average cash inflow each customer of a homogeneous customer segment pays for the service per period), the higher the probability of repeat purchases of the complainant in the next period. Hogreve and Gremler (2009) support the assumption made in the simulation model that the probability of repeat purchases in the next period is at 100% if the monetary amount of the complaint solution equals or exceeds the price a customer paid. On the other hand, if there is no complaint solution, the probability is set to 0%. The model makes the simplification that the value of a complaint solution equals its monetary amount. In practice, there are not only purely monetary but also other tangible and intangible measures for complaint solutions (see Andreassen 1999, Mattila and Wirtz 2004, Smith et al. 1999). Since these measures also cause direct or indirect expenses, this simplification can be justified.

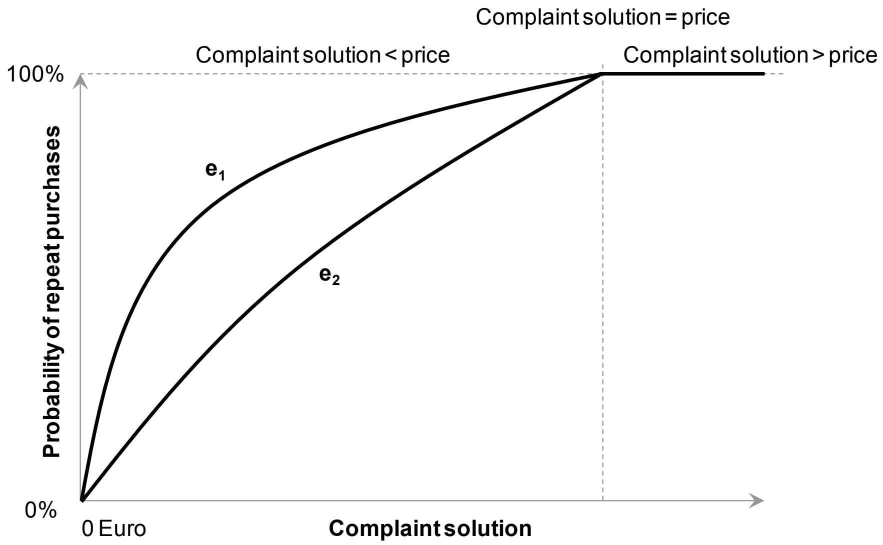

Figure 3-2: Probability of repeat purchases

The expectations of the homogeneous customer segment are captured using the parameter *expectation level e* (ϵ [0, 1]) that characterizes the probability of repeat purchases between the two defined extreme values. As Figure 3-2 for a low (e_1) and a high (e_2) expectation level exemplarily shows, a higher expectation means that the probability of repeat purchases is lower in the customer group with higher expectations (e_2) for an identical complaint solution. An expectation level of 0 implies that this customer group would purchase the service in the next period in any case – irrespective of the monetary amount for the complaint solution and the price of the service. An expectation level of 1 means that the customer group would only be fully satisfied once the complaint solution reaches the monetary equivalent of the price paid for the service (see equation 5).

$$\left(\frac{s(t)}{p(t)}\right)^{e(t)} = \begin{cases} \left(\frac{s(t)}{p(t)}\right)^{e(t)} & , 0 \leq s(t) < p(t) \\ 1 & , s(t) \geq p(t) \end{cases} \tag{5}$$

If both complaint solution and expectation level have the value 0 at the same time, a 100% probability of repeat purchases is assumed. This can be justified by the fact that the complaint solution should be irrelevant for customers without expectations. Further information on how to influence the expectations of customers can be found in Arens (2004) and Oliver (1980).

As in section 3.1.1 motivated, the *Customer Equity CE* ($\epsilon\ \mathbb{R}$) is used to quantify cause-and-effect relationships between complaint management and company value whereby only the relevant part is considered, that is, the Customer Equity of the modeled (homogeneous) customer group. This parameter is directly influenced by the number of existing customers and the corresponding revenues and expenses. The aspired minimization of loss of Customer Equity is achieved by a maximization of the model parameter Customer Equity.

The inflow *revenues u* ($\epsilon\ \mathbb{R}_0^+$), increases the Customer Equity (see equation 6). It is calculated by multiplying the number of existing customers and the price. Thereby it is assumed that revenues immediately become effective cash items.

$$u(t) = EC(t) * p(t) \tag{6}$$

By contrast, the two outflows *expenses for complaint solutions q* ($\epsilon\ \mathbb{R}_0^+$) and *other expenses o* ($\epsilon\ \mathbb{R}_0^+$) reduce the Customer Equity. While expenses for complaint solutions can be calculated by a simple multiplication of the number of complainants and the monetary amount for one complaint solution (equation 7),

$$q(t) = f(t) * s(t) \tag{7}$$

the parameter other expenses covers all payments occurring in order to deliver the service. It contains both variable cash outflows for an individual customer and expenses for the creation of the whole service offering for the homogeneous customer group. In the model, this parameter is simply calculated as the multiplication of the number of existing customers and the average *other expenses per customer v* ($\epsilon\ \mathbb{R}_0^+$).

$$o(t) = EC(t) * v(t) \tag{8}$$

The parameter *interest rate z* (ϵ [0, 1]) represents the company-internally defined opportunity costs at which capital – and hence Customer Equity – has to be valued.

Equation 9 shows the corresponding calculation of the realized Customer Equity in period t.

$$CE(t) = (CE(t-1) + u(t) - q(t) - o(t)) * (1 + z(t)) \tag{9}$$

Thus the goal conflict is included on how to use available capital for complaint solutions or invest it in other areas.

3.1.3.2 Model Behavior

The model contains a negative feedback loop that is characterized according to the general notation with a minus sign. This implies a goal-seeking system behavior. Due to the only outflow churn rate, the number of customers can only be reduced – as required for the isolated analysis of the complaint behavior. A certain share of existing customers voices complaints. In the next period, these complainants either defect to a competitor or repeat their purchase of the service with a certain probability depending on the monetary equivalent amount of the complaint solution. At this point, the feedback effect occurs: The lower the number of existing customers, the lower the number of complaints of dissatisfied customers in future periods. The number of complainants is declining.

If the model parameters price, expectation level, and complaint solution are constant, the multiplication operator (see equation 3) implies a decreasing churn rate. Thus, in absolute terms more customers will defect in the first periods of the simulation. This number decreases over simulation time. The exact number of existing customers at the end of the simulation and its impact on the minimization of the loss of Customer Equity is examined in the next section.

3.1.3.3 Simulation and Scenario Analysis

Table 3-3 shows the parameter instantiations used for the base case simulation. They are fictitious and rely on logical considerations in order to clearly prove the importance of the customer lifetime. An evaluation of the model with realistic data follows in section 3.1.3.4.

Using these parameter values and equation (1), the CLV of a customer in the examined customer group is calculated to be 476.99 Euro. A simulation using Vensim shows that the optimal monetary equivalent of the complaint solution is 31.16 Euro. If this optimal value is chosen, the Customer Equity reaches its maximum at 4.516 million Euro.

Table 3-3: Definition of parameters for the base case

Parameter	Instantiation
Existing customers EC	10,000 customers
Price p	140.05 Euro
Other expenses per customer v	90.00 Euro
Expected customer lifetime d	10 months
Expectation level e	40.0%
Complaint rate r	5.0%
Interest rate z	3.0%

Literature suggests that the duration of a customer relationship has decisive influence on the company value (Reichheld and Sasser 1990). Thus it seems likely that a purely aggregate consideration of the customer value as main determinant for the calculation of the optimal monetary amount of a complaint solution, as suggested by Baker and Collier (2005), falls short.

Table 3-4: Optimal monetary amount for the complaint solution for selected parameters

Expected Customer lifetime d (in months)	Interest rate z (in %)	Net cash flow (p – v) (in Euro)	CLV[4] (in Euro)	Optimal complaint solution s* (in Euro)
Interest rate and CLV constant				
10	3.0	50.05	476.99	31.16
20	3.0	30.04	476.96	45.82
60	3.0	16.63	476.87	85.50
120	3.0	14.29	476.90	104.26
Expected customer lifetime and CLV constant				
10	3.0	50.05	476.99	31.16
10	5.0	54.69	476.99	35.37
10	10.0	66.76	476.97	46.72
Net cash flow and CLV constant				
10	3.0	50.05	476.99	31.16
20	10.0	50.05	476.15	97.08
60	11.7	50.05	477.27	140.04

[4] Due to the requirement for integer periods and the limit to two decimal places in the net cash flow, the CLV slightly deviates from the desired value of 477.00 Euro.

Therefore it is important to undertake a detailed examination of the individual parameters influencing the CLV. Table 3-4 shows that a (nearly) identical CLV can be caused by different combinations of customer lifetime, interest rate, and net cash flow (the difference between price and other expenses per customer). However, the (optimal) amount for a complaint solution varies significantly.

These results indicate that in a dynamic environment the determination of the complaint solution using a static defined CLV is not sufficient. This result does not only have theoretical implications regarding the work of Baker and Collier (2005), but also practical impact on the relevant content for Business Intelligence systems and accompanying data warehouses or data marts for complaint management. This will be discussed in more detail in section 3.1.3.4.

Sensitivity Analysis

Figure 3-3 shows how both the optimal complaint solution and the maximum Customer Equity (resulting if the optimal complaint solution is chosen) change if the examined parameters of complaint management are individually increased or decreased by 10% (compared to the instantiations in the base case) without changing the other parameters (ceteris paribus consideration). Thus, the model reacts with a different sensitivity to changes of the four depicted parameters.

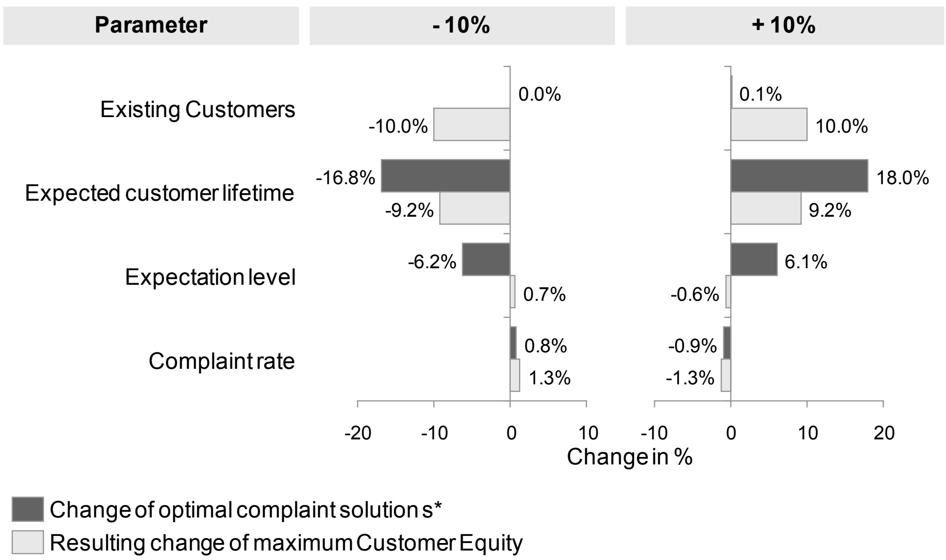

Figure 3-3: Sensitivity analysis of core parameters

The number of *existing customers* has been added to cross check the model's logic. Because interdependencies are omitted within a homogeneous customer group, the Customer Equity has to grow proportionally with the number of existing customers.

This is confirmed by the results of the sensitivity analysis. The deviation of 0.1% for the optimal complaint solution is explained by rounding impreciseness.

The strongest influence on simulation results is caused by a change of the *expected customer lifetime*. This parameter change leads to an over-proportional adaption of the payment for the optimal complaint solution and a (nearly) proportional adaption of the Customer Equity. The latter can be explained by an altered duration for the cash inflows (less interest rate effects and defection risk). On the contrary, the over-proportional change of the payment for the optimal complaint solution is surprising and shows the importance of the length of a customer's relationship with the company.

The *expectation level* influences mainly the payment amount for the optimal complaint solution but not – conditionally to the optimal choice of the complaint solution – the maximum amount of the Customer Equity (+0.7% or -0.6%). Hence, a change of the expectation level leads only to a relocation of the optimal combination of the payment for the complaint solution and the resulting probability of repeat purchases (see Figure 3-2).

The simulation model is quite robust regarding a change of the *complaint rate*. Both complaint solution and Customer Equity change by not more than 1.3%.

The described results can prove useful especially for an operationalization of the simulation model based on parameter values stemming from already available, company-specific data.

3.1.3.4 Critical Reflections and Limitations

The proposed model to determine the optimal payment amount for a complaint solution applying a value-oriented management view has to be evaluated regarding the formulated requirements in section 3.1.1. This ensures that the contribution fulfills both scientific relevance (“rigor”) and practical relevance (“relevance”).

Requirement (1) Applicability to a class of problems

The proposed simulation model does not contain any industry-specific restrictions. Hence, it can be applied to different kinds of services, such as financial, communicational, or informational services. However, it is limited by the assumptions the model is based upon. The probably strongest assumption is the necessity for periodical revenues. But even then, there still are numerous scenarios that fulfill that requirement in the real world, such as the use of credit cards, mobile phone tariffs, or media subscriptions (newspapers, journals, television).

The practical applicability of the model further requires the availability of all relevant input parameters.

Table 3-5 shows an estimation of data availability. It is complemented by the following excursus that shows the exemplary application for a mobile operator.

Table 3-5: Estimation of data availability

Parameter	Availability by customer segment	Origin	Description of possible sources
Existing Customers EC	High	Sales	Customer segmentation based on revenues or contribution margin analyses
Price p	High	Sales	Customer segmentation based on revenues or contribution margin analyses
Other expenses per customer v	High	Controlling	Variable costs, information on allocation of overhead cost
Expected customer lifetime d	Medium	Marketing	Historical experience, statistical analyses, consideration of customer age and/ or duration of product lifecycle
Expectation level a	Medium	Marketing	Market research on customer loyalty and behavior of competitors
Complaint rate r	Medium	Customer service	Calculation based on number of calls (call center), emails and personal complaints
Interest rate z	High	Finance	Company-internal given discount rates (e.g., WACC)

Excursus: Exemplary application for a mobile operator

In Germany, 2.6 million mobile phone cards have been used exclusively for data transmission in 2009 (Bundesnetzagentur 2009). Since then, their number has increased significantly (Mohr et al. 2010, van Damme et al. 2010). UMTS data tariffs are typically not volume-based but sold as so-called flat-rates that cost between €19.90 and €39.95 and can be cancelled at the end of each month (Telespiegel 2010). Hence, the required assumption of a periodical revenue model can be regarded as fulfilled.

To minimize the loss of value due to defecting customers, subsequently only that part of the customer base is taken into account that buys the UMTS flat-rate but no other products. Although this assumption might seem restrictive on first view, it does not influence the model's applicability to more than one product. This simplification only serves to improve comprehensibility.

For this exemplary application a company with 25% market share for customers with mobile Internet usage via notebook and UMTS is assumed. 10% of these customers solely have a UMTS flat-rate that can be cancelled at the end of each month. Corresponding to the German Statistical Ministry (Statistisches Bundesamt 2009) and Mohr et al. (2010) this equals about 65,000 customers. Each customer pays a monthly fee of €20.00. The company has calculatory expenses of €18.00 per month and customer. Furthermore, an interest rate of 8% – typical for that industry (Funnell and George 2010) – and a customer group independent complaint rate of 1% are assumed. The expectation level is set to 40%.

Based on socio-demographic factors and company-internally available data, data mining techniques (such as data cluster analysis) reveal five homogeneous customer groups into which the 65,000 customers can be divided. Their expected remaining customer lifetime varies according to Table 3-6.

Table 3-6: Example for a mobile operator

Customer group	**1**	**2**	**3**	**4**	**5**
Existing Customers	3,800	10,200	16,500	14,800	19,700
Expected customer lifetime (in months)	12	24	36	48	60
Optimal complaint solution s* (in Euro)	0.82	2.65	5.18	8.24	11.76
Customer Equity for s* (in Euro)	94,292	471,609	1,132,000	1,345,000	2,236,000
Customer Equity for s = 5.00 Euro (in Euro)	93,816	470,676	1,132,000	1,330,000	2,168,000

Applying the simulation model, significant differences through the optimal choice of the amount of the complaint solution can be observed. The reason is the strong influence of the remaining customer lifetime. The hereby realizable Customer Equity deviates in sum by €84,409 compared to a lump-sum of €5.00 for all customers.

Requirement (2) Innovative contribution on the published knowledge base

The results of the literature review in section 3.1.2 showed that there is no contribution that fulfills all three specific requirements as described in section 3.1.1: (A) providing a monetary result for the complaint solution, (B) being transparent regarding the compliance of and support for value-based management, and (C) considering dynamic effects.

The simulation model previously presented fulfills these requirements and, hence, contributes to an extension of the existing body of knowledge.

Ad requirement (A): The model returns as result a monetary value for the optimal amount of a complaint solution considering a maximization of the Customer Equity as objective.

Ad requirement (B): In section 3.1.1 was showed that the target variable Customer Equity can be used as a measure for the value of a company. All direct and indirect relationships affecting the Customer Equity are made transparent by the modeled causal relationship in the stock and flow diagram (depicted in Figure 3-1 by + or -). Thereby, the underlying mental decision model is explicated.

Ad requirement (C): The model considers the dynamic effects described in section 3.1.3.1. It could be even shown that published analytical approaches such as Baker and Collier (2005) are too undifferentiated for certain cases. The simulation results in section 3.1.3.3 prove that the unreflected use of the customer value as parameter might be misleading since single components of the CLV, especially the remaining customer lifetime, influence the result significantly.

Requirement (3) Comprehensible justification and validibility

The presented contribution addresses a socio-technical system with a big number of factors that factually exclude a deterministic solution. Hence, the simulation model is formally not verifiable due to its very nature.

Since these kinds of problems are typical for business information systems and engineering, the acceptance of artifacts by experts, being aware of the state-of-the-art in research and practice, based on argumentations or implementations is accepted by the scientific community (Österle et al. 2010).

The simulation model described in section 3.1.3.1 is based on the published body of knowledge or arguments based thereupon. Hence, it should be inter-subjectively comprehensible for an expert of business information systems and engineering.

A further step towards validation would be an implementation of the simulation model using the multi case study approach according to Yin (2009). Different business units would have to be compared regarding their value contribution over a multi-year period whereby one group of business units would strictly follow the recommendations of the simulation model. The other group of business units would continue with their current practice regarding decisions for complaint solutions. A split-up of a homogeneous customer segment into a test group and a comparison group could be also done in theory, but is likely to prove problematic in reality due to the unequal treatment of equivalent customers. Apart from the fact that reliable results can be expected at the earliest in about three to five years, it has to be considered that such studies will be error-prone to environmental influences such as fads in customer preferences and problems such as a source-related revenue allocation.

Requirement (4) Future benefit for stakeholders

The model has both theoretical implications (for scholars) and practical implications (primarily for decision makers in complaint management in the service industry).

Theoretical implications

As discussed above for requirement 2C, the simulation showed that a differentiated consideration of the parameters used for calculating the CLV can lead to other results than previously published in literature. This indicates that the topic "optimal amount of a value-oriented complaint solution" is not yet sufficiently understood – especially if dynamic effects are not neglected.

Specifically in the context of the recent strong growth of online social networks, an exciting extension would be the in-depth examination of so-called word-of-mouth effects for the optimal complaint solution. Although initial approaches such as Meier and Reinwald (2010) already exist, these could be extended based on the proposed simulation model.

The proposed model can be adapted and extended flexibly. Possible examples include an increase of the complaint rate due to opportunistic customer behavior or increased loyalty due to a satisfying reaction to a complaint. This is an advantage compared to more restrictive analytical model and facilitates the transferability to and feasibility in practice.

Practical implications

The model helps decision makers to understand the effects of changes in external parameters, such as complaint rate or expectation level, compared to changes in company-internal parameters, such as the interest rate, on the optimal payment amount for a complaint solution.

Furthermore, relevant measures for incentive schemes of decision makers outside of complaint management can be motivated, since, for example, an increased customer loyalty resulting in a longer customer lifetime measurably increases the company value. On the other hand, a change of the expectation level does not imply a significant change in the Customer Equity – provided that the payment amount for a complaint solution has been adjusted according to the proposed model.

Critical reflections and outlook

Despite promising findings, the presented model is also beset with limitations. First, the model examines only one homogeneous customer group per simulation run. This allows only a very isolated view on the impact for the Customer Equity. Also, interactions between customer groups are not considered. Second, there are numerous other factors in customer relationship management that might be responsible for a change of the number of customers (e.g., new customer acquisitions from marketing). In terms of a holistic model, these factors should also be considered to prevent a potential misleading recommendation due to the optimization of isolated single factors. Section 3.2 will present another System Dynamics model that already includes parts of these factors. Third, model and insights are based on constant parameter values. However, the methodology used offers the possibility to integrate distributions to model realistic variations (e.g., for the churn rate) and/or developments (e.g., continuous price erosion due to increasing competitive pressure). Fourth, the influence of a price change on volume (i.e., the number of customers) is neglected. In principle, it could easily be integrated by using a price-demand function.

The proposed simulation model for determining the optimal payment amount for a complaint solution in the service industry shows fundamental relationships. It also can serve as rudimentary discussion basis for further research. Therefore, it is the goal to extend this initial model step by step towards the conditions of the real world: (1) Further evaluation of model structure and assumptions using case study research, (2) relaxation of the assumptions, and (3) extension of the focus.

Ad (1): By using contacts to the complaint management department of both a personal computer manufacturer and an online retailer, the goal is to implement the model in selected business areas and compare the results with business areas that have not used the model.

Ad (2): The model is based on some restrictive or simplifying assumptions, such as a repeat purchase rate of 100% in case of a payment amount equal to or above the price of the service, a periodical revenue model, and a negligible share of customers pursuing an opportunistic strategy. Such assumptions should be relaxed as much as possible.

Ad (3): In addition, there are many other factors in the area of complaint management that influence the Customer Equity. One of these are word-of-mouth effects. This area is becoming especially important due to the dynamic development of so-called online social networks. Thus, the nature and the strength of customer connections in online social networks might significantly influence the optimal payment amount for a complaint solution – in addition to the CLV and its elements as discussed. The goal is to include these and other effects in terms of a module concept to the proposed basic model, so each of the modules can be refined independently, ideally, without causing changes in other modules.

3.1.4 Application of the I²RDM Method[5]

This section applies the I²RDM method proposed in chapter 2 to the previously presented decision support model for complaint management. Although the model is very simple, all steps can theoretically be scaled to match the complexity of real-world settings as System Dynamics models with more than 100 variables confirm (Sterman 2000).

The model assumes periodic revenues from a homogeneous customer segment as they can be found for data tariffs in the telecommunication sector. The central issue for the decision maker is the conflict between loss in company value due to defecting customers (churn) and loss in company value due to overinvestment in customer retention.

Subsequently, the procedure model of the I²RDM method (presented in Figure 2-1) is applied to identify the importance of measures and derive a prioritization.

Step A: Identify top key measure. The company strives for sustainable value increase. A suitable top key measure for complaint management is the Customer

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5 Section 3.1.4 is, except for marginal changes in details, identical with section 5 of Mosig (2012), a paper written by the author of this dissertation and published in the Proceedings of the 45th Hawaii International Conference on System Sciences.

Equity (CE), an aggregated measure representing the sum of values of all customers (quantified by their customer lifetime value). Following a value-based management approach, CE should be maximized (or a loss of CE minimized).

Step B: Delineate area of responsibility. The complaint manager only decides on the amount of compensation paid as a complaint solution. Since, for instance, acquisitions of new customers are outside the decision maker's area of responsibility, marketing efforts or the number of new customers do not have to be part of the model.

Step C: Model causal relationships. Decision maker and business analyst jointly identify causal relationships. Figure 3-4 shows the resulting causal loop model for the example.

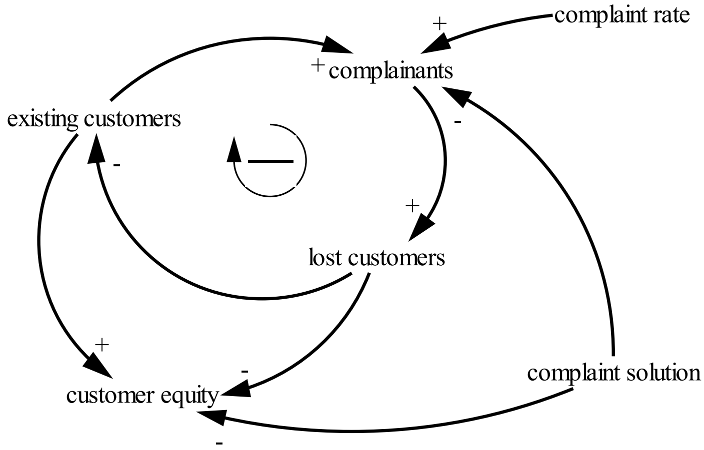

Figure 3-4: Causal loop diagram of the System Dynamics model for complaint management

The higher the number of *existing customers*, the higher the *customer equity* will be. But at the same time, more customers imply a higher number of *complainants* since typically a certain fraction of customers complains (*complaint rate*). But the *complaint solution* required to reduce the number of complainants also reduces the *customer equity*. On the other hand, the more *complainants* remain unsatisfied, the more customers a company may lose (*lost customers*), which also would reduce the *customer equity*.

Step D: Model stock and flow diagram. The causal model is translated into a stock and flow diagram (see Figure 3-1). The stock *existing customers* contains in each period the respective number of customers. Since acquisition was excluded the stock cannot grow but only be reduced by the flow *churn rate* – representing the part of customers defecting. The churn rate is influenced by four converter parameters: the *price* paid for a service, the number of customers complaining in each period (*com-*

plainants), the amount of a (monetary) *complaint solution*, and the *expectation level* the customers have regarding the complaint solution.

The cause-and-effect relationship between complaint management and company value is modeled via the stock *customer equity*. It is increased by *revenues* (existing customers pay each period a price for the service) but decreased by *expenses for complaint management* (the complaint solutions paid to the complainants) and by *other expenses* (representing the production cost of a service).

Step E: Formulate simulation model. Differential equations, realistic parameters and initial conditions need to be defined for all model elements. Existing System Dynamics tools – as e.g. Vensim® DSS 5.9e – allow equations drawing from an extensive set of functions and distributions. In the complaint management example, the equations are justified by previous research results and empirical observations. Typical parameter values from the telecommunication industry are used to instantiate the model.

Step F: Validate simulation model. Prior to interpreting results, the model's validity must be examined. While the exemplary model passes structure tests (as dimensional consistency checks) and structure-oriented behavior tests (as feasible model behavior in case of applying extreme values), a behavior pattern test (as matching model predictions with the observed reality) or an empirical confirmation have not yet been published.

Step G: Prioritize measures based on sensitivity analysis. In order to determine the importance of measures, the effect of a parameter change of +/–10% on required corrective actions of the only decision parameter (complaint solution) and on the top key measure CE are simulated. This coincides with the two main purposes of measure-based reporting: ex-ante decision support and ex-post controlling (Euler et al. 2010). Figure 3-5 shows the results of this numerical sensitivity analysis for most stock and converter elements. Valve elements and converter elements purely calculated from other converters are excluded. The reason is that in this case a change of +/–10% may be caused by different variations of upstream model elements. This is not considered as a bug but as a feature since it fosters systems thinking and requires a decision maker to focus on the root cause of an effect instead of relying on measures that are difficult (and hence error-prone) to interpret. Nevertheless, these measures might be used if upstream measures cannot (easily) be reported. In the example, the *churn rate* may be used as a fair proxy for the *expectation level* because a +/–10% variation of the *expectation level* results in a +5.3%/–5.9% change of the *churn rate*.

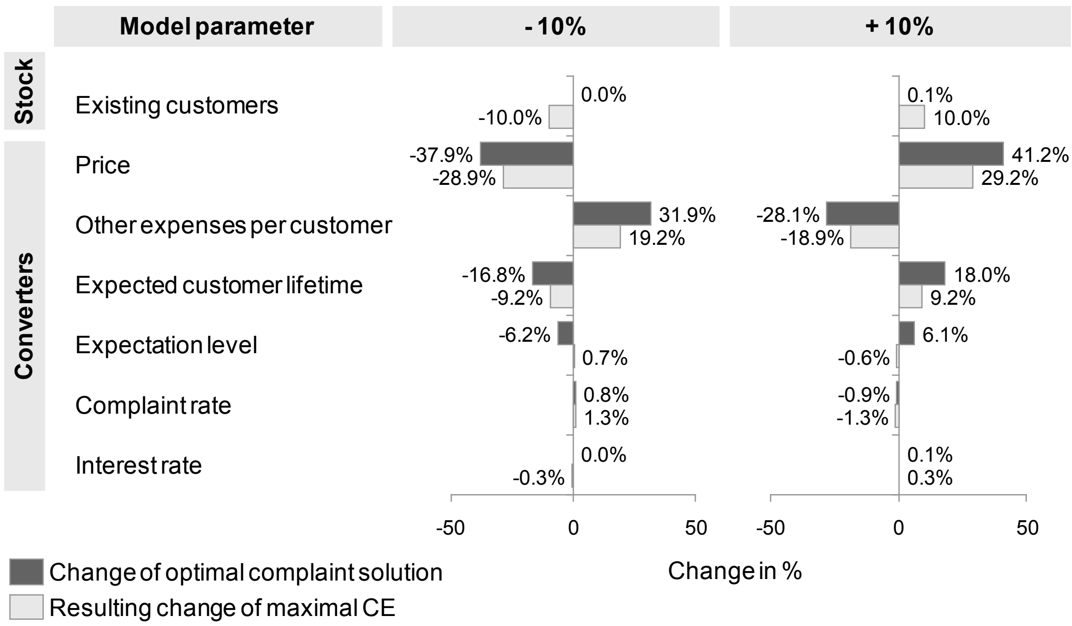

Figure 3-5: Numerical sensitivity analysis of the System Dynamics model for complaint management

For prioritization purposes, three classes are distinguished: under-proportional (less than 5% change), about proportional (between 5 and 15% change), and over-proportional (more than 15% change) influences on either the top key measure or the necessary adjustment of the decision parameter. Data availability is selected as second dimension and split into three classes: low (manual or semi-manual data collection), middle (online availability), and high (online availability in high data quality and frequency).

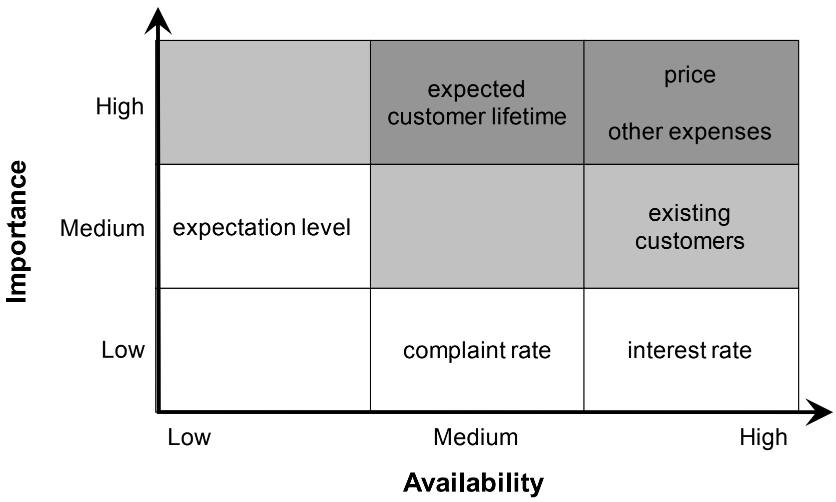

Figure 3-6: Resulting prioritization matrix of the System Dynamics model for complaint management

In the example, the company adopts the prioritization matrix: Importance is higher valued than availability. Figure 3-6 shows the resulting matrix for measures of the example. Judgment of data availability follows the assumptions explicated in section 3.1.3.4. Measures resulting from valves may be added if they substitute a measure with low availability but high or medium importance (as in this case *churn rate* instead of *expectation level*). Note that the *customer equity* as top key measure is not part of the prioritization but should be reported as well, while the decision parameter (*complaint solution*) is not reported.

In summary, the example shows the feasibility of the suggested method to identify and prioritize information needs regarding operational and repetitive decisions in principle. It especially helps to emphasize on the right non-financial measures (in this case *expected customer lifetime*, *expectation level*, or *complaint rate*) instead of often lagging financial measures (Euler et al. 2010) as *revenues* or *expenses*.

3.2 System Dynamics Model for Word-of-Mouth Effects[6]

The importance of considering word-of-mouth (WOM) effects in marketing research has been acknowledged for decades. However, decision makers still face the problem that their mental models lack clarity in their overall interaction. Negative and positive word-of-mouth effects have mostly been studied in isolation. They have been examined in the context of either customer acquisition or retention. However, the interplay between the antecedents and consequences of word-of-mouth has often been excluded. Hence, section 3.2 proposes an integrated model based on existing scientific findings in order to show the ecosystem's inherent dynamics owing to the various interrelationships caused by word-of-mouth effects. As integrating link, the paradigm of value-based management is adopted.

Three well-established marketing research streams are combined into a dynamic model. First, analytical models determining the optimal budget allocation between acquisition and retention efforts serve as basis. Second, both expectancy-disconfirmation theory and exit-voice theory are used to model complaint management as the central part of retention efforts. Third, the model is extended by word-of-mouth-triggered feedback effects. Owing to contradictory empirical findings, different scenarios are used to simulate dynamic implications.

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6 Sections 3.2.1 to 3.2.3 were written in collaboration with the supervisor of this dissertation, Prof. Dr. Marco C. Meier, and Dr. Dieter Reinwald (FIM Research Center) and are, except for marginal changes in details, identical with FIM working paper WI-394 (Mosig et al. 2012).

From a scientific point of view, the model may serve as a hypotheses generator for empirical marketing researchers. Practitioners benefit from an improved mental model that helps them to value the magnitude and possible consequences of word-of-mouth effects.

The structure of the next sections is as follows. After a motivation of the business demand (section 3.2.1), an overview of related work simulating word-of-mouth effects and a justification of the chosen simulation method, theoretical background on which the model is based is presented (section 3.2.2). The development of the model itself then follows the core-shell research design depicted in Figure 3-7 (section 3.2.3.1). First, Customer Equity (CE) as the integrating link is modeled. Then, the optimal budget allocation between acquisition and retention efforts is added using an analytical model. Based on the expectancy-disconfirmation theory and exit-voice theory, complaint management as the central part of retention efforts is modeled in more detail. Finally, word-of-mouth-triggered feedback effects are added. Furthermore, the model behavior is examined by analyzing the causal loops of the model (section 3.2.3.2). As part of an evaluation, scenarios are developed and used to simulate the dynamic implications (section 3.2.3.3). A critical reflection, a discussion of limitations, and suggestions for future research are presented in section 3.2.3.4. Finally, the I²RDM method is applied to the System Dynamics model for word-of-mouth effects (section 3.2.4).

3.2.1 Business Demand

In the hotel sector, about fifty percent of bookings stem from recommendations (Stokes and Lomax 2002). Coca Cola found out that not only more than 30 percent of dissatisfied complainants no longer buy their products, but also that they told on average 9 people about their negative experiences (TARP 1981). Both examples show the potential influence of positive and negative word-of-mouth effects for the economic success of companies. Overall, estimates claim two-thirds of the U.S. economy to be affected by word-of-mouth effects, of which about 13% are driven strongly and 54% partially (Dye 2000).

Over the last years, the growth of online social networks (OSN), such as Facebook, and the rise of new technologies, such as high-speed mobile networks and smart phones, yielded to an interactive and participatory Internet with ubiquitous access (Dean et al. 2012). Facebook crossed the mark of 500 million monthly active users in July 2010 and reached the 900 million mark in March 2012, over half of whom log in on any given day (Ebersman 2012). On average, each user creates 90 pieces of content per month and distributes them among 130 friends (Facebook 2011). Consequently, the interconnectedness of customers has risen dramatically (Allsop et al. 2007; Karakaya et al. 2011). Experiences with emotionally charged goods or services can be discussed and shared instantly with a large and rapidly increasing number of customers. While on the one hand, these developments suggest a further growing influence of word-of-mouth effects on attention-prone goods or services in the near future, on the other hand, the availability of high-quality social network data offers new possibilities for companies to monitor and manage word-of-mouth effects (Libai et al. 2010).

These facts indicate that word-of-mouth effects are increasingly crucial for the success and, therefore, in the long run for the survival of companies. Consequently, the importance to incorporate word-of-mouth effects to understand marketing interactions and appropriately value customer relationships (Anderson 1998) has been repeatedly acknowledged (Allsop et al. 2007; Anderson 1998; Dichter 1966; Libai et al. 2010; Reichheld and Sasser 1990; Villanueva et al. 2008). Word-of-mouth thereby “refers to informal communication between private parties concerning evaluations of goods and services” with a positive, negative, or neutral valence (Anderson 1998, p. 6; Dichter 1966). Despite numerous investigations, there is still a surprising lack of clarity with regard to the dynamics caused by word-of-mouth effects from a company perspective. So far, negative and positive word-of-mouth have mostly been studied in isolation, and word-of-mouth effects have been assigned to either customer acquisition or retention efforts. So, the dynamic interplay between the antecedents and consequences of word-of-mouth has not yet been sufficiently examined (Karakaya et al. 2011).

The goal of the System Dynamics model is to get new insights into the basic question of how company success is influenced by word-of-mouth and take steps toward quantification of word-of-mouth effects to better understand the magnitude of their implications. Therefore, a System Dynamics model is proposed that integrates the knowledge of existing scientific findings and theories. The model itself contributes to enhancing transparency in the decision processes connected with word-of-mouth. Furthermore, from a scientific point of view, development of the model as well as the simulation results may systematically reveal further gaps of knowledge and serve as generator of new hypotheses for ongoing empirical research.

The model is based on a design-oriented deductive approach. Figure 3-7 summarizes the research design. The focus lies on the explanation stage in the ongoing repetitive research cycle of description (“understand”), explanation (“design”), and testing (“evaluate”), defined by Meredith et al. (1989).

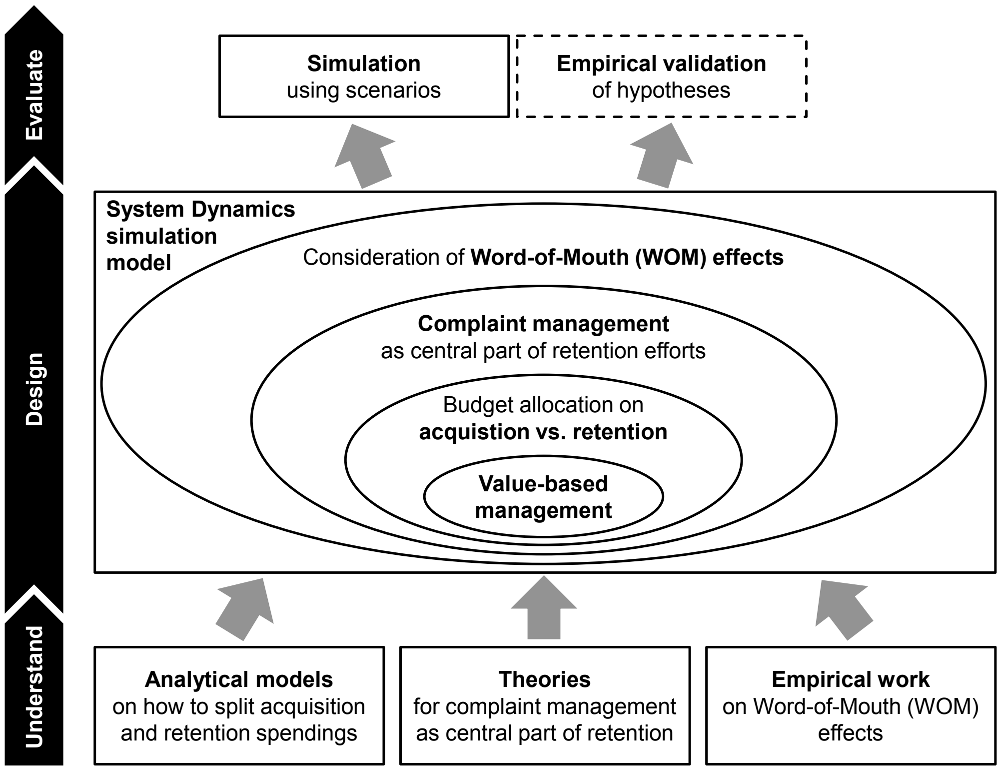

Figure 3-7: Research design of the System Dynamics model for word-of-mouth effects

In order to "understand" the problem and interrelations between model elements, reference is made to three established marketing research streams from literature as theoretical foundation: first, analytical decision models on the optimal spending split between customer acquisition and retention; second, the expectancy-disconfirmation theory (Oliver 1980) as well as exit-voice-loyalty theory (Hirschman 1970) as two central theories for complaint management; and third, empirical work on word-of-mouth effects.

The "design" of the simulation model starts with a general kernel containing the overall business goal, and is enhanced and detailed step by step in three shells. The creation of business value is a key issue for the success of companies and therefore accepted in many investigations as the top goal from a business administration point of view (see, e.g., Lee et al. 2006). Consequently, the core element in our model refers to value-based management and integrates all other model parts. Value orientation has been defined as "a concretization of the shareholder value approach with the long-term objective to maximize the net present value of all future cash flows" (Gneiser 2010, p. 96). To operationalize value orientation in the marketing domain, the concept of customer lifetime value (CLV) has been proposed. It is defined as "the present value of the expected benefits (e.g., gross margin) less the burdens (e.g., direct costs of servicing and communicating) from customers" (Dwyer 1997, p. 7). While the CLV addresses the valuation of a single customer relationship, the concept of customer equity (CE) has been proposed to measure the value potential of the whole customer base (including existing and potential customers). It can be regarded as an aggregated CLV. Over the last years, both concepts have been increasingly used as criterion for decision making (Gneiser 2010; Gupta and Zeithaml 2006; Holm et al. 2012), as many models and approaches show (see e.g., Berger and Nasr-Bechwati 2001; Blattberg et al. 2001; Blattberg and Deighton 1996; Meier and Reinwald 2010).

In the second shell (see Figure 3-7), model elements are added to understand the key issues of budget allocation decisions involving investments on new customers (acquisition) and existing customers (retention). In the third shell, the retention part is worked out in more detail with focus on complaint management, because it addresses customer satisfaction. Since it is generally accepted that word-of-mouth is largely driven by one's satisfaction or dissatisfaction with a product or service (Anderson 1998; Mangold et al. 1999), word-of-mouth effects are finally incorporated into the model.

Although the focus is on the explanation stage, some effort is made to "evaluate" the model. After having applied both structural and behavioral tests for model validation (Barlas 1996; Barlas 1989), the model is simulated using a scenario approach. Furthermore, new hypotheses are derived for empirical validation through experiments using feasible parameter settings. Empirical tests do not form part of this model.

3.2.2 Theoretical Background

The theoretical background decomposes into two parts. At first, related work regarding the simulation of word-of-mouth effects is analyzed. Second, necessary groundwork from marketing research is presented.

Simulation of Word-of-Mouth Effects

While extensive empirical studies have been made on the antecedents and consequences of word-of-mouth effects, only very few prescriptive approaches tried to quantify these effects (Hogan et al. 2004). Simulation has been proposed as a method to both study the dynamics of marketing and make predictions (Jager 2007). With regard to marketing simulation methods, System Dynamics and agent-based modeling have been proposed (Rand and Rust 2011). In the following paragraphs, the general feasibility of System Dynamics to model word-of-mouth effects is indicated and differences to agent-based modeling are distilled, thereby the superiority of System Dynamics over agent-based modeling for the purpose of this model is shown.

The idea to use System Dynamics to shed light on word-of-mouth research emerged about 30 years ago. As one of the first authors in this field, Morecroft (1984) introduces word-of-mouth effects in terms of diffusion of new technologies considering feedback loops. He finds that word-of-mouth effects are an essential element in the diffusion process. Sterman (2000) describes word-of-mouth effects considering the bandwagon effect. Positive and negative word-of-mouth effects make people follow specific attitudes of another person, an effect that is often observed in political elections and the diffusion of new products. Sterman (2001) also provides another example for word-of-mouth effects in which he demonstrates how word-of-mouth effects influence the transfer of potential adopters into the adopter population. As done in this model, he integrates the assumptions about communication behavior based on empirical data to substantiate the effects. Pavlov and Saeed (2004) base their work on a limits-to-growth pattern to create a word-of-mouth archetype that considers reinforcing effects. They apply the archetype in a technological peer-to-peer network for online file sharing. As in this model, new customers influence the acquisition of new customers. Bianchi and Bivona (2002) address the word-of-mouth effects in the strategic e-commerce domain. They consider them from both a reinforcing and balancing perspective. The reinforcing loop is characterized by an increasing customer base due to investments. The balancing loop emerges owing to negative word-of-mouth reducing the customer base and is caused by a decreasing website quality (e.g., performance issues). Another example is provided by Meier and Reinwald (2010), who investigate the repurchase behavior of two different customer groups influenced by word-of-mouth effects.

Although a broad acceptance for modeling word-of-mouth effects using System Dynamics can be found, agent-based modeling approaches have recently gained importance (Libai et al. 2010). Several authors investigate them to simulate the behavior of individual customers and their interactions (Allsop et al. 2007; Bonabeau 2002; Karakaya et al. 2011; Ono et al. 2003). Libai et al. (2010) provide an overview of different publications using agent-based modeling to represent and simulate customer-to-customer interactions. In order to demonstrate social systems as adaptive complex systems, they simulate “would-be worlds” in which customers interact with each other. Agent-based modeling approaches are able to grasp the full complexity of interpersonal relationships as well as non-linear behavior. Hence, agent-based modeling is applied more and more in social sciences in general as well as in marketing research (Allsop et al. 2007; Rand and Rust 2011).

For this model, System Dynamics was selected as simulation method for two reasons. First, the focus on a holistic integrated model combining scientific findings requires a homogeneous customer segment and assumes an average customer behavior. System Dynamics supports this level of abstraction. Agent-based modeling, however, requires an accurate formulation of decision processes of individual customers. Second, an analysis of the feedback loops based on a causal loop diagram of the problem reveals a high number of feedback loops. Owing to interdependencies embedded in the proposed integrated model for the effects of word-of-mouth on customer acquisition and retention, the system's complexity (measured in terms of interconnected causal loops) explodes once word-of-mouth effects are considered. As will be shown in section 3.2.3.2, there are six feedback loops involving positive word-of-mouth effects, ten feedback loops involving negative word-of-mouth effects, and 14 feedback loops involving both. As a result, the number of customers, the major driver of company value, is influenced by 23 feedback loops (compared to only seven in a model that does not take into account word-of-mouth effects). Also, in this case System Dynamics is more suitable than agent-based modeling when it comes to analyzing these feedback loops and understanding their impact on company value.

Both System Dynamics and agent-based modeling concur in their analysis that traditional analytical models are widely incapable of comprehending the real-world richness of dynamic word-of-mouth effects (Rand and Rust 2011). However, the holistic and aggregated System Dynamics perspective inevitably abstracts from individual behavior. Agent-based modeling approaches could complement this shortcoming and provide additional insights into complex customer behavior by modeling individuals with their personal preferences and decision processes. Hence, a combination of System Dynamics and agent-based modeling (as suggested by Schieritz 2002 and Scholl 2001) could compensate for System Dynamics's disadvantages in these respects and add another perspective for modeling and quantifying word-of-mouth effects in the future.

Related Work

The simulation model builds on groundwork from three marketing research streams. First, an analytical decision model for the optimal budget split between customer acquisition and retention is selected. Second, the expectancy-disconfirmation theory (Oliver 1980) and exit-voice-loyalty theory (Hirschman 1970) are introduced as two central theories for complaint management. Third, key insights from empirical work on word-of-mouth effects are considered.

Analytical decision models on the optimal budget allocation between acquisition and retention efforts serve as starting point. The quest for the right balance in this marketing resource allocation problem has been extensively examined from various angles. A well-established framework stems from Blattberg and Deighton (1996), who address the question of how much to invest in acquisition or retention. Their isolated view is enhanced by Berger and Nasr-Bechwati (2001), who present a decision model to determine the optimal split for a fixed promotional budget between acquisition and retention. Reinartz et al. (2005) further extend both approaches and empirically strengthen Blattberg and Deighton’s proposition of decreasing returns for investments in both acquisition and retention. They also confirm the existence of a ceiling for these spendings (Reinartz et al. 2005). Hence, the central assumptions of the analytical models of Blattberg and Deighton and Berger and Nasr-Bechwati can be regarded as empirically sufficiently affirmed and generally accepted.

Since the model’s purpose is to simulate word-of-mouth effects and satisfaction is the key driver of word-of-mouth (Mangold et al. 1999; von Wangenheim and Bayón 2007), complaint management as the most central aspect in retention efforts (Fornell and Wernerfelt 1987) is examined in more detail. In general, complaint management targets “transforming dissatisfied customers back into satisfied customers in order to stabilize endangered customer relationships” (Reinwald 2009, p. 2), because retaining existing customers needs less effort than acquiring new ones (see e.g., Mittal and Kamakura 2001). In order to measure the impact of customer retention, focusing on the aspect of customer satisfaction and behavior, Stauss and Seidel characterize the main goal of complaint management as “increasing the profitability and competitiveness of the organization by restoring customer satisfaction, minimizing the negative effects of customer dissatisfaction on the organization” (Stauss and Seidel 2004, p. 30). This aspect is strengthened by Conduit and Mawondo (2001), who argue that organizations need to understand their customers’ expectations in order to satisfy them. Customers become dissatisfied when there is a discrepancy between their ex-ante expectations (or prior attitude) and ex-post perceptions (Churchill and Surprenant 1982; Oliver 1980). Oliver (1980) provides an empirical model that expresses customer satisfaction as a function of expectation and expectancy disconfirmation (known as expectancy-disconfirmation theory). To model the full “life cycle” of customers, reference to the exit-voice-loyalty theory is made (Hirschman 1970). This theory states that if customers become dissatisfied, they will choose one of three options. They withdraw from the customer relationship (“exit”), attempt to improve the situation by suggesting changes or voicing their complaint (“voice”), or do nothing and accept the situation (“loyalty”).

With regard to word-of-mouth effects, there still is a surprising lack of unambiguous and universally valid findings. To cope with this issue, frequently cited and repeatedly affirmed findings were included directly in the model while contradictory or arguable results were considered in the scenario analysis. For example, Mangold et al. (1999) suggest that negative word-of-mouth is twice as likely as positive word-of-mouth.

While Anderson (1998) confirms that negative word-of-mouth is typically stronger, he further notes that the difference might not be as big as thought. Wangenheim and Bayón (2007) suggest that customers might be especially valuable shortly after their first purchase. This can be explained by customers trying to convince themselves about their buying decision (Dichter 1966), but is contradictory to the widely shared belief introduced by Reichheld and Sasser (1990) that profits from referrals increase over time.

Several effects have been identified regarding the modeling of the antecedents and consequences of word-of-mouth. For instance, both newly acquired customers and satisfied complainants tend to spread positive word-of-mouth (Anderson 1998; Dichter 1966; Mangold et al. 1999; TARP 1981; von Wangenheim and Bayón 2007). In contrast, exiting customers and defecting complainants spread negative word-of-mouth (Anderson 1998; Mangold et al. 1999; von Wangenheim 2005). Furthermore, word-of-mouth affects both acquisition and retention (Anderson 1998; Hogan et al. 2004; Lee et al. 2006; von Wangenheim and Bayón 2007; von Wangenheim 2005).

3.2.3 System Dynamics Model

3.2.3.1 Model Structure

Value-based Management

The use of CE as central criterion in business decision making is nowadays well accepted in customer relationship marketing (Berger and Nasr-Bechwati 2001). Since we build upon frameworks and analytical models that use CE directly (Berger and Nasr-Bechwati 2001; Blattberg and Deighton 1996), we will as well use it as measure to compare different scenarios. CE has typically been defined as the total cash inflow CF_{in} less the total cash outflow CF_{out} over all customers and periods T discounted by an interest rate i (see equation 10).

$$CE = \sum_{t=1}^{T} \frac{(CF_{in})_t - (CF_{out})_t}{(1+i)^t} \tag{10}$$

The same idea is used in the System Dynamics model (see Figure 3-8), but instead of discounting future cash flows, they are summed up over time. The stock *customer equity*[7] is used to compare the results of different simulation runs.

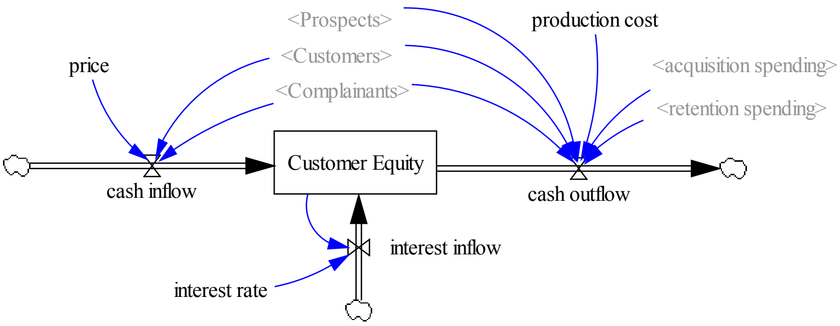

Figure 3-8: Financial partial model covering value-based management

Cash inflow results from the number of existing customers (defined as the sum of *customers* and *complainants*) and the *price* paid for a product or service. *Cash outflow* is determined by the *production cost* of a product or service for each existing customer, the *acquisition spending* for each *prospect*, and *retention spending* for each existing customer. The *interest rate* determines the *interest inflow* which also increases the customer equity over time.

Customer Acquistion versus Customer Retention

Following Blattberg and Deighton's (1996) argumentation, a company sells a single product or service on a regular basis, for example, once a year. This assumption translates into a periodic revenue model for a company with one homogenous customer segment. By keeping the model that simple, an abstraction from other marketing problems beyond our research focus is made (e.g., the correct marketing expense allocation for multiple products) without impeding its general applicability and the possibility for later refinement (Blattberg and Deighton 1996). Furthermore, the assumptions of Berger and Nasr-Bechwati (2001) are adopted, who examine a company operating in a closed, monopolistic ecosystem with a fixed promotional budget available for acquisition and retention efforts.

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7 Strictly speaking, CE is always a discounted value representing the current value of all current and future customers. Because this logic cannot be implemented in the System Dynamics model although the stock customer equity can be easily transformed into the "true" economic CE through a simple division by $(1+i)^t$, we kept the term to emphasize the model's compliance with this concept.

Subsequently, the research streams in marketing are interlinked to build a stable system. A system is regarded as stable when it finds its equilibrium; that is, the number of customers in each stock is stable when it converges. The model is designed as a closed system with a fixed number of persons. Each person is exclusively included in one of the stocks, *prospects*, *customers*, or *complainants*. In this section, the balance between acquisition (*new customer rate*) and retention (the sum of *defection rate* and *exit rate*) is modeled to regulate the flow between the prospects and existing customers (modeled as two stocks, *customers* and *complainants*). In the next section, work from complaint management explains the calculation of the *defection rate* and *satisfaction rate* (expectancy-disconfirmation theory) and the *voice rate* and *exit rate* (exit-voice-loyalty theory). In the last step, word-of-mouth effects based on four antecedents and three consequences are added.

Following Blattberg and Deighton (1996), concave (downward) shaped acquisition and retention functions are assumed with company- and industry-specific maxima for the share of prospects that can be acquired (*acquisition ceiling* a_c) and the share of existing customers that can be retained (*retention ceiling* r_c). The *acquisition ratio* a is determined from *acquisition spending* A and calculated as follows:

$$a = a_c * (1 - e^{-k_1 * A}) \text{ with } k_1 = (-1) * \frac{\ln\left(1 - \frac{a_0}{a_c}\right)}{A_0} \tag{11}$$

Here, a_0 denotes the *current acquisition ratio* achieved by investing the *current acquisition spending* A_0. In order to initially get the required parameter values a_0, A_0, and a_c, decision calculus is used, “in which managers’ judgment and/or estimates serve as some of the inputs to formal modeling” (Berger and Nasr-Bechwati 2001, p. 49). This method helps managers to break down complex problems into smaller elements and has been proved suitable to translate real-world problems into formal models (Blattberg and Deighton 1996).

The *retention ratio* r is calculated accordingly. Again, the *current retention ratio* r_0, *current retention spending* R_0, and *retention ceiling* r_c serve as input parameters to determine the shape of the retention function (see equation 12).

$$r = r_c * (1 - e^{-k_2 * R}) \text{ with } k_2 = (-1) * \frac{\ln\left(1 - \frac{r_0}{r_c}\right)}{R_0} \tag{12}$$

Berger and Nasr-Bechwati (2001) extend this model to analytically determine the optimal budget split. They assume a fixed *promotional budget* B (per person) that has to cover both acquisition and retention spending of a company. While the company’s *retention spending R* is used for measures addressing each existing customer (*customers C_1* and *complainants C_2*), its *acquisition spending A* is used for measures addressing all the *prospects P* (Berger and Nasr-Bechwati 2001) (see equation 13).

$$B = \frac{R * (C_1 + C_2) + A * P}{C_1 + C_2 + P} \tag{13}$$

Following the insurance example case of Berger and Nasr-Bechwati (2001) and using analytically optimized input parameters for *R* and *A*, a stable system is obtained. The left-hand side of Figure 3-9 shows the corresponding part in the stock-and-flow diagram.

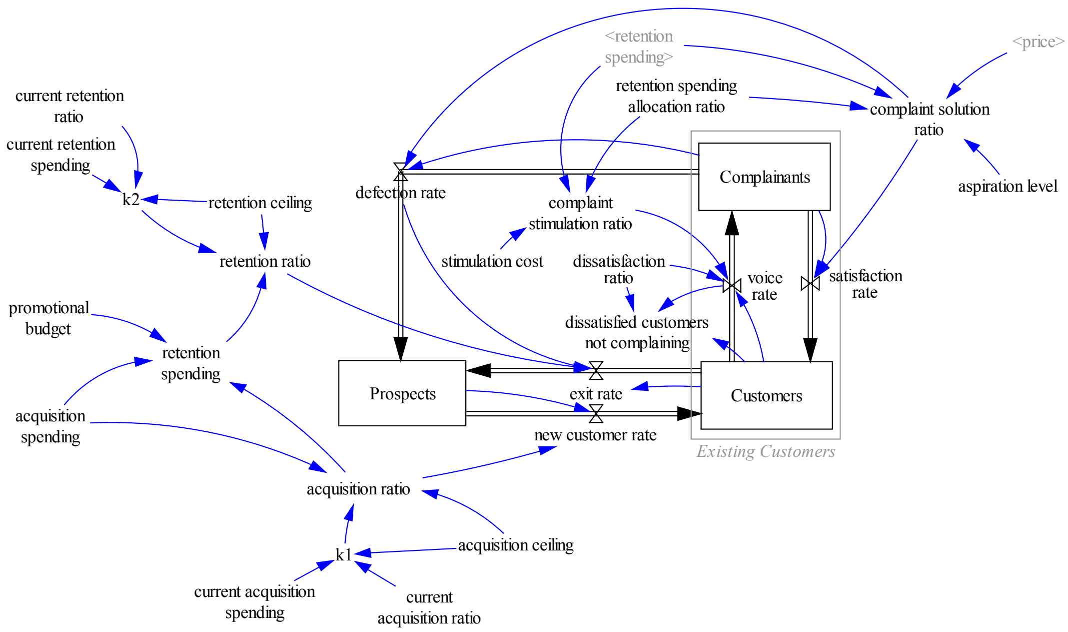

Figure 3-9: Customer partial model covering the areas customer acquisition versus customer retention and complaint management

Complaint Management

The aim of complaint management is to transform all unsatisfied complainants back into satisfied customers. This section explains the calculation of the *defection rate* and *satisfaction rate* (based on the expectancy-disconfirmation theory) and the *voice rate* and *exit rate* (based on the exit-voice-loyalty theory). The *retention spending allocation ratio* determines the monetary split between both parts in the model. One part of the *retention spending* is used to offer a *complaint solution* to a *complainant*, while the other part is used to stimulate *dissatisfied customers* to voice their complaints (defined as *complaint stimulation ratio* in the model). For the sake of simplicity, it is assumed that a company selects the most effective measures and uses their monetary equivalent in the model.

The expectancy-disconfirmation theory is used to justify the underlying assumption. The literature suggests that an unsatisfied customer will definitely be satisfied if the *complaint solution c* is equal or above a certain threshold (Hogreve and Gremler 2009) – in our case, the *price p*. Furthermore, if no complaint solution is offered, we assume that the customer remains unsatisfied and defects in the next period. The probability of a customer between these two extreme positions staying loyal depends on his or her *aspiration level e (t)*. This parameter allows considering different expectations (e.g., depending on the importance of a product or service for a customer group). Following Meier et al. (2011), for a given compensation (in the model, the complaint solution's monetary equivalent), a higher retention probability is assumed for complainants with a lower aspiration level and a lower retention probability for complainants with a higher aspiration level. Thus, this parameter determines the shape of the *complaint solution ratio* function *s* (see equation 14).

$$s\,(t) = \left(\frac{c}{p}\right)^{e\,(t)} = \begin{cases} \left(\frac{c}{p}\right)^{e\,(t)} & ,0\ \le c \le p \\ 1 & ,c \ge p \end{cases} \tag{14}$$

A decision maker decides via the *retention spending allocation ratio* on the monetary amount available for the complaint solutions. This impacts the *complaint solution ratio* and, consequently, the complainant retention ratio (modeled as *satisfaction rate*). The higher the compensation paid (ceteris paribus), the higher is the probability of complainant retention for the next period.

In order to combine the previously introduced work on optimal promotional budget allocation (for both acquisition and retention spending) and complaint management, the problem that customer churn is not completely explained by failed complaint management needs to be solved. Hence, as second part of the retention model, reference is made to Hirschman's (1970) exit-voice-loyalty theory, which says that the *dissatisfaction ratio* determines the overall share of dissatisfied customers. Depending on a company's complaint stimulation efforts, a certain share of customers voice their complaints (*voice rate*). The cost to offer the required complaint channels are covered by the *stimulation cost*. Hence, the *retention spending allocation ratio* determines how many dissatisfied customers a company can identify (*complaint stimulation ratio*) who will turn into *complainants* (to be addressed by complaint management efforts). Unstimulated dissatisfied customers are assumed to either stay loyal (and remain in the *customer* stock) or exit. This development must be matched with the overall retention ratio a company observes. Hence, in the model the sum of the *exit rate* and *defection rate* equals the overall retention ratio. Stauss and Seidel (2008) also refer to this theory when they call attention to the hidden and unvoiced complaints by defining the “customer annoyance iceberg.” As in their argumentation, decision makers in this model can only indirectly influence the exit rate.

While the model in this respect is admittedly rather simple, this does not impede its suitability to simulate word-of-mouth effects, since the resulting system is once again stable; that is, the number of customers in each stock converges. As a result, the basic stock-and-flow diagram can be derived (see Figure 3-9) and linked to value-based management. The left-hand side of the customer partial model shows the acquisition versus retention logic, while the right-hand side presents the complaint management logic. Using the described theories to determine the initial parameter values, the expected stable system behavior is achieved that serves as reference when examining the complex dynamic interactions of word-of-mouth effects.

Word-of-Mouth Effects

To account for possible industry-, company-, or culture-specific characteristics, four antecedents and three consequences of word-of-mouth are added. Their strength is determined by parameter values and based on different assumptions in scenarios.

Both *positive WOM recipients* and *negative WOM recipients* are modeled as separate stocks (see Figure 3-10). These store the number of persons who are influenced by a positive or negative experience of other persons. Note that it is do not distinguished between prospects and existing customers since both groups are assumed to be equally approached by word-of-mouth. Furthermore, it is assumed that word-of-mouth occurs mainly when a person changes from one state (e.g., complainant) to another (e.g., customer). This assumption is backed by empirical findings that reject a linear model but show an asymmetric U-shape for the relationship between customer satisfaction and word-of-mouth (Anderson 1998).

To calculate the *increase of negative WOM,* first the average number of *persons approached by the exiting customers* is multiplied with the average number of *dissatisfied customers not complaining* (but at most the actual *exit rate*[8]) and then the average number of *persons approached by the defecting complainants* is multiplied with the actual *defection rate*. Then, both are added up. According to Wangenheim (2005), dissatisfied customers defecting from a company engage more often in

[8] If the number of *dissatisfied customers not complaining* is higher than the *exit rate*, the dissatisfied customers not exiting are assumed to stay loyal and turn into “normal” customers again in the next period. In the model, they simply stay in the customer stock.

negative word-of-mouth than the customers exiting for other reasons (e.g., price sensitivity). Hence, the average number of persons approached should be higher for defecting complainants than for exiting customers. For example, dissatisfied customers can be expected to tell nine persons about their bad experience (Mangold et al. 1999). Another example states that more than 25% of switching customers in the telecommunication industry transmit negative word-of-mouth to one to up to 40 persons (on average 3.36) (von Wangenheim 2005).

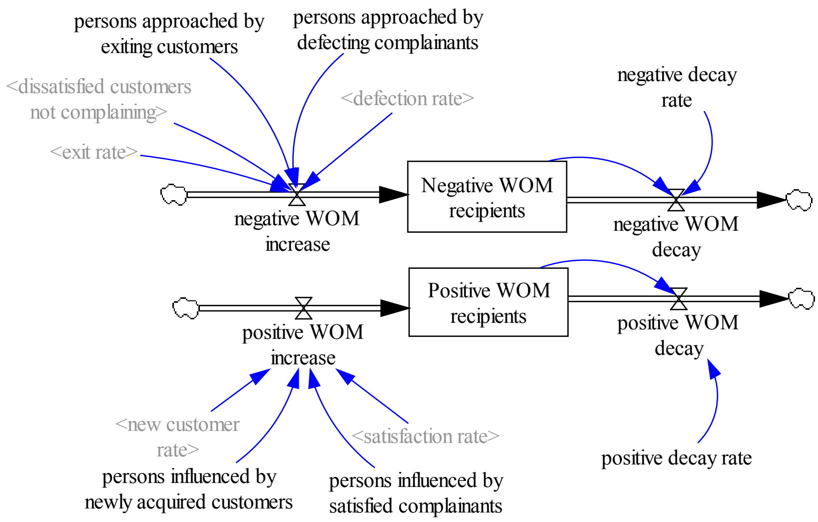

Figure 3-10: Word-of-mouth partial model covering the antecedents of word-of-mouth effects

To calculate the *increase of positive WOM,* first the average number of *persons influenced by newly acquired customers* is multiplied with the actual *new customer rate* and then the average number of *persons influenced by satisfied complainants* is multiplied with the actual *satisfaction rate*. Then, both are added up. The first part depends on the strength of the described post-purchase self-justification effect (Dichter 1966; von Wangenheim and Bayón 2007), while the second part accommodates the observation that positive word-of-mouth is more likely to be spread by customers greatly satisfied with complaint handling than by customers without that experience (TARP 1981). For example, a study from consumer services discovered that satisfied customers are likely to tell five other persons about their good experience (Heskett et al. 1997; Lee et al. 2006).

Trusov et al. (2009) found that word-of-mouth effects have substantially longer carryover effects than traditional marketing actions. Therefore, the stock elements also serve as memory that “forgets” at a speed set by the decay rate. In the model, the rate was set to 0.9 for the outflow of each stock. This means that 10% of negative/positive word-of-mouth recipients will remember the good or bad experience they were told the previous period.

The consequences of word-of-mouth are fed back into the model on three points. It is “typically assumed that WOM works through attitude change” (von Wangenheim and Bayón 2007, p. 238), which increases or decreases the likelihood of goods or services being selected (Bone 1995; Herr et al. 1991). This attitude change is modeled by a dynamic adjustment of the maximum number of prospects that can be acquired (*acquisition ceiling*), the maximum number of existing customers that can be retained (*retention ceiling*), and the expectation level complainants have when approaching the company for a complaint solution (*aspiration level*).

The arctangent function is used to model these consequences. This matches the idea behind existing empirical models that use Tobit models (Anderson 1998), logit models (Lee et al. 2006; von Wangenheim 2005; von Wangenheim and Bayón 2004), or extensions based on them (von Wangenheim and Bayón 2007). This function is compressed to restrict the obtained values to the interval [-1; 1] and multiplied with a delta ceiling value Δ representing the range the default value is allowed to fluctuate. Hence, the default value can be increased (decreased) by the delta value if all persons in the system receive positive (negative) word-of-mouth. Note that the model contains the assumption that a positive and a negative message annihilate each other. Equation 15 shows the implemented formula for the dynamic *acquisition ceiling* $a_c(t)$ whereby *PWOM* denotes the number of *positive WOM recipients*, *NWOM* the number of *negative WOM recipients*, and $a_{c_{default}}$ the *default acquisition ceiling*. The *retention ceiling* $r_c(t)$ is calculated accordingly.

$$a_c(t) \ = \arctan\left(\frac{PWOM\ (t) - NWOM(t)}{C_1\ (t) + C_2(t) + P(t)}\right) * \frac{2}{\pi} * \Delta_{a_c} + a_{c_{default}} \tag{15}$$

For the *aspiration level* $e(t)$, only the number of *negative WOM recipients* is considered (see equation 16). The underlying assumption is that the expectations of complainants will be lower if they have received negative word-of-mouth. On the contrary, positive word-of-mouth do not increase one’s expectations above the default level.

$$e(t) \ = \arctan\left(\frac{NWOM(t)}{C_1\ (t) + C_2(t) + P(t)}\right) * \frac{2}{\pi} * \Delta_e + e_{default} \tag{16}$$

Figure 3-11 shows the full stock-and-flow diagram. It consists of the described three parts and shows their interconnection. Shadow variables have been used for readability.

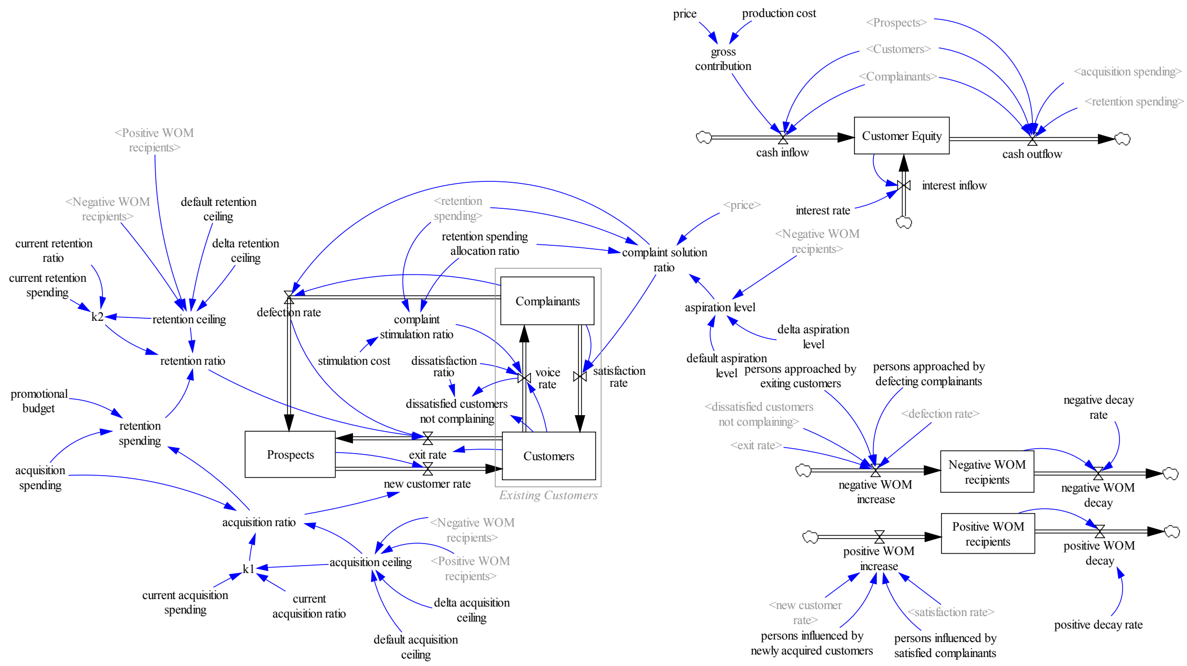

Figure 3-11: Overall stock-and-flow diagram showing the consequences of word-of-mouth effects

First, customer perspectives show the flow of persons within the system. This part of the system causes word-of-mouth and is at the same time affected by it. Second, the word-of-mouth perspective captures the positive and negative messages exchanged between persons. It is a kind of remembering, since persons also remember what they have been told weeks or even months ago. Third, the financial perspective incorporates value-based management views in the model. Customer equity is used as the ultimate measure to determine the magnitude of word-of-mouth effects on a company's value.

3.2.3.2 Model Behavior

This section presents the underlying assumptions required and interdependencies embedded in the proposed integrated model for the effects of word-of-mouth on customer acquisition and retention. It shows that the system's complexity (measured in terms of interconnected causal loops) explodes once word-of-mouth effects are considered.

The model contains a number of feedback loops concerning word-of-mouth effects. Since the measure for our analysis is the *Customer Equity* it is modeled as a dependent variable. In reality, two other causal relationships from *Customer Equity* to *Acquisition* and *Retention* would have to be added since a company would reinvest in customer acquisition and/or retention in the long term (dotted causal relationships in Figure 3-12). This would yield to additional feedback loops. Due to the focus on word-of-mouth effects and the assumed fixed promotional budget, this dynamic effect has been excluded. Instead the analytical approach of Berger and Nasr-Bechwati (2001) has been used to determine the optimal spending level.

Figure 3-13 and 3-13 depict the model structure – first without, then with word-of-mouth effects – and how the consideration of positive and negative word-of-mouth effects leads to an explosion of feedbacks loops.

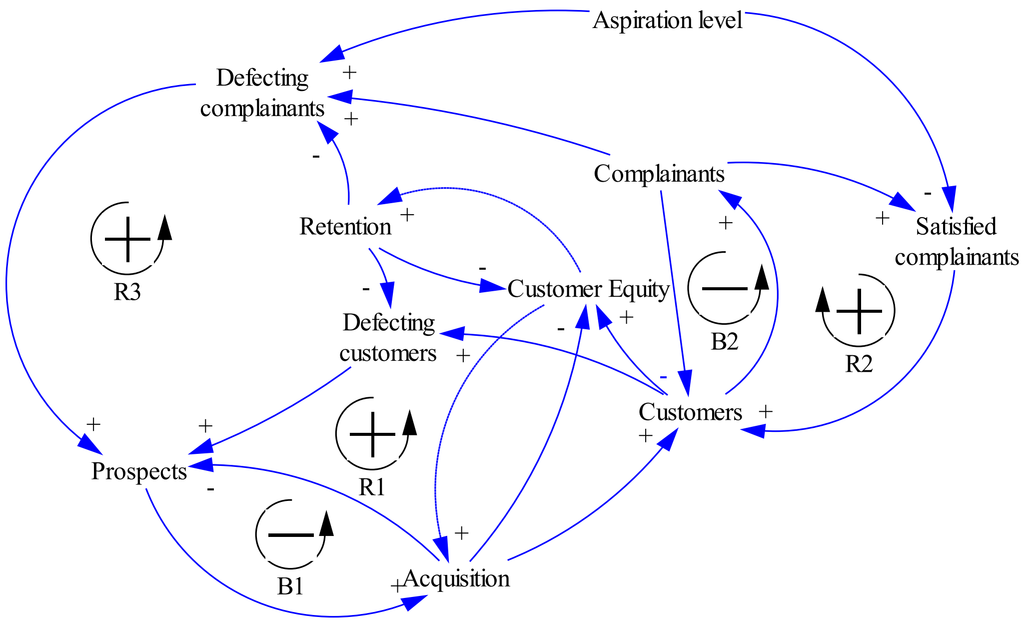

Figure 3-12: Causal loop diagram without consideration of word-of-mouth effects

Without considering word-of-mouth effects (Figure 3-12) the basic model consists of three main reinforcing loops and two main balancing loops. The first balancing loop B1 limits the number of potential new customers (*Prospects*) and ensures a fixed number of people in the system. Otherwise, the reinforcing loop R1 would lead to an infinite growth of people in the system. R1 is partly caused by the fact that higher efforts in *Acquisition* lead to a higher number of *Customers*, partly by the adoption of the exit-voice theory (Hirschman 1970). Unsatisfied customers either voice their dissatisfaction and become *Complainants* or leave the company and become *Defecting customers*. In a closed ecosystem, defecting customers again become *Prospects*. The reinforcing loops R2 and R3 are explained by the expectancy-disconfirmation theory (Oliver 1980). In both loops, the number of *Customers* drives the number of unsatisfied customers (*Complainants*). A growing number of *Complainants* implies also a growing share of *Satisfied complainants* which become *Customers* again (R2).

It also implies a growing share of *Defecting complainants* that become *Prospects* again (R3). Both reinforcing loops are balanced by loop B2 because an increase in *Complainants* also causes a decrease in *Customers*.

In Figure 3-13, word-of-mouth effects were added based on four well-accepted antecedents and three consequences. The underlying assumptions are that newly acquired customers (*Acquisition*) and *Satisfied complainants* spread positive word-of-mouth (Anderson 1998; Dichter 1966; Mangold et al. 1999; TARP 1981; von Wangenheim and Bayón 2007). *Defecting customers* and *defecting complainants* spread negative word-of-mouth (Anderson 1998; Mangold et al. 1999; von Wangenheim 2005). Word-of-mouth affects the *Acquisition*, *Retention*, and *Aspiration level* (Anderson 1998; Hogan et al. 2004; Lee et al. 2006; von Wangenheim 2005; von Wangenheim and Bayón 2007).

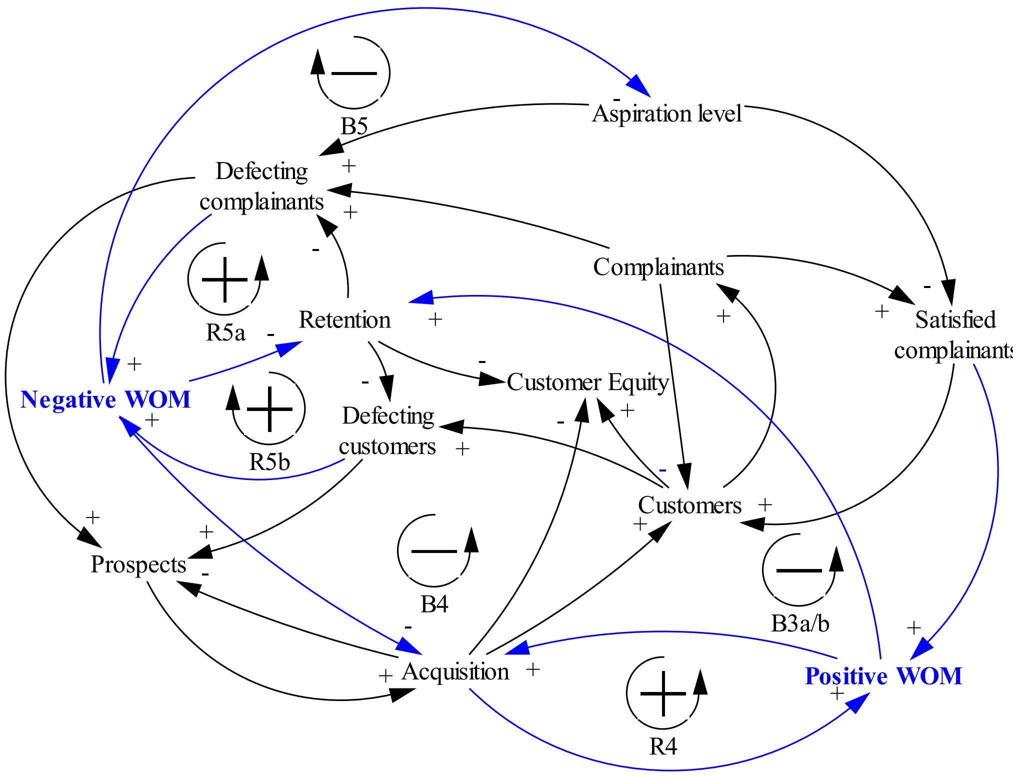

Figure 3-13: Causal loop diagram with consideration of word-of-mouth effects

The number of causal loops explodes if *Positive WOM* and *Negative WOM* are added. All in all, there are six new feedback loops involving *Positive WOM*, 10 new feedback loops involving *Negative WOM* and 14 new feedback loops involving both. As a result, the variable *Customers* as the major driver of *Customer Equity* is now influenced by 23 feedback loops (compared to only seven in the model without word-of-mouth effects).

The seven most direct feedback loops caused by word-of-mouth effects result directly from the modeled antecedents and consequences. So leads *Positive WOM* to more *Acquisition* which in turn increases *Positive WOM* (reinforcing loop R4) since they try to reconfirm themselves of their buying decision (Dichter 1966). Furthermore, *Positive WOM* also increases the likelihood of *Retention* thereby reducing the number of *Defecting complainants* and *Defecting customers* which limits the number of *Prospects* in the closed ecosystem*; Acquisition* is hence limited and the increase of *Positive WOM* declines (balancing loops B3a/b). *Negative WOM* is balanced by two loops. *Negative WOM* reduces *Acquisition* and via the chain from *Customers* to *Complainants* the number of *Defecting complainants* as a major cause for *Negative WOM* (B4). Due to the expectancy-disconfirmation theory (Oliver 1980) a higher amount of *Negative WOM* also reduces the *Aspiration level* thereby reducing the number of *Defecting complainants* and in turn *Negative WOM* (B5). But there are also two reinforcing loops because *Negative WOM* reduces the likelihood of *Retention* thereby increasing the number of *Defecting complainants* and *Defecting customers* that in turn increase *Negative WOM* (R5a/b).

The remainder of the feedback loops emerges due to overlaps of the described main loops. To better understand the inherent dynamic caused by the various intertwined loops, the next section presents a corresponding simulation.

3.2.3.3 Simulation and Scenario Analysis

For simulation, the insurance example case of Berger and Nasr-Bechwati (2001) is used. The example is characterized by 1,000,000 persons, a promotional budget of \$30 per person, and a gross contribution of \$100 per period. Furthermore, their assumptions on the acquisition and retention functions are adopted; gross contribution and interest rate are slightly modified. The resulting non-linear programming problem to find a new optimal allocation was solved using the Generalized Reduced Gradient (GRG) method in the Excel solver function. As a result, a system is obtained that finds its equilibrium after about five periods. Hence, the total simulation time is set to 10 periods (using a time step of 0.015625). This seems reasonable, as all scenarios stabilize within this timeframe (see Figures 6–8). For complaint management, assumptions are added that the dissatisfaction ratio is 0.3 (own assumption), the retention spending allocation ratio 0.7 (own assumption), and the aspiration level 0.4 (following Meier et al. 2011). As simulation software Vensim® DSS 5.9e is used.

Table 3-7: Word-of-mouth assumptions for different scenarios

Scenario	❶ Base case without WOM	❷ Weak WOM effects	❸ Strong WOM effects
Persons approached by dissatisfied exiting customers	0	1	3
Persons approached by defecting complainants	0	3	7
Persons influenced by newly acquired customers	0	1	2
Persons influenced by satisfied complainants	0	1	3

Table 3-7 summarizes the assumptions used for the strength of word-of-mouth antecedents. Note that in both word-of-mouth scenarios, the number of persons addressed owing to negative experiences is twice the number addressed owing to positive experiences. The assumptions regarding consequences are that the *acquisition ceiling* varies in the interval [0.3; 0.9] and the *retention ceiling* lies within [0.55; 0.95]. However, these extremes are rather theoretical owing to the used arctangent function. For example, if each person in the system receives one positive word-of-mouth message more than negative word-of-mouth messages, the *acquisition ceiling* is set to 0.75 instead of the default value of 0.6 – that is, half of the possible delta acquisition ceiling ratio. Positive word-of-mouth would have to outnumber negative word-of-mouth by at least the factor five in order to set the value near its maximum. Although this behavior could be altered by introducing a factor alpha in the equations for word-of-mouth consequences to cause a faster or slower convergence to extreme values, it has been omitted for reasons of simplicity and missing empirical evidence. The *aspiration level* is allowed to fluctuate within [0.2; 0.4] owing to negative word-of-mouth.

The resulting company value varies significantly. In the first scenario, the stock *customer equity* reaches $145.56M after period 10 compared to $149.89M in the second scenario and $153.17M in the third scenario. This effect is rather surprising, since negative word-of-mouth is transmitted to twice as many persons as positive word-of-mouth. It is mainly caused by differences in the development of existing customers (first scenario: 297,765; second scenario: 298,993; third scenario: 300,042), which is due to variations in the acquisition/retention ceilings and aspiration levels. Figure 3-14, Figure 3-15, and Figure 3-16 show the development of these measures.

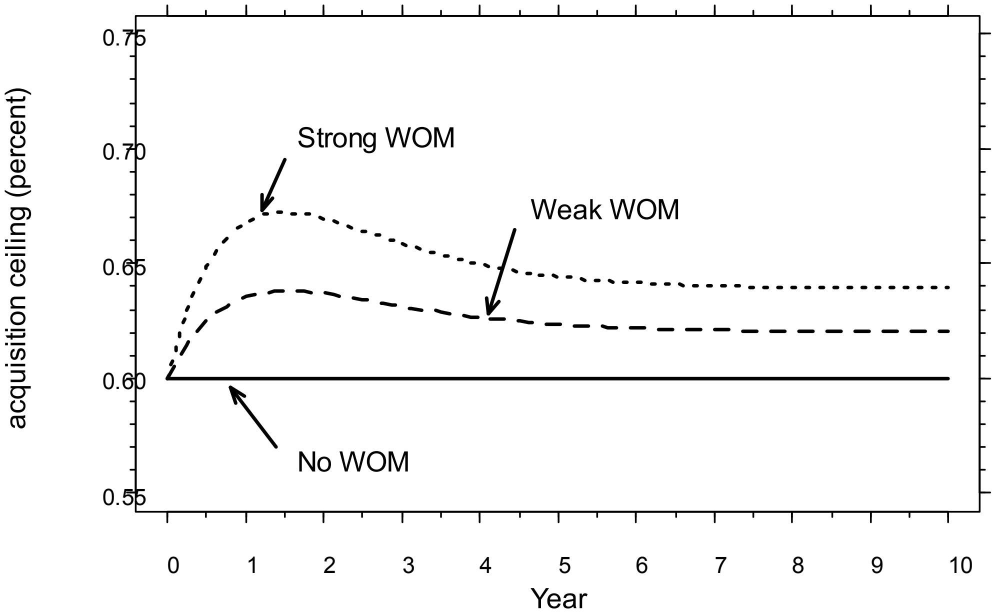

Figure 3-14: Development of acquisition ceiling

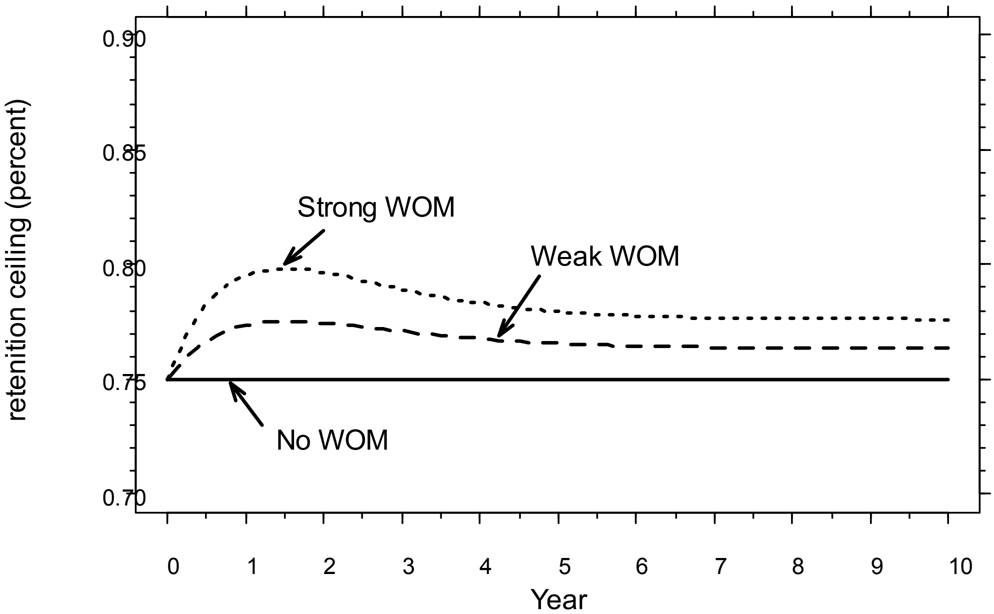

Figure 3-15: Development of retention ceiling

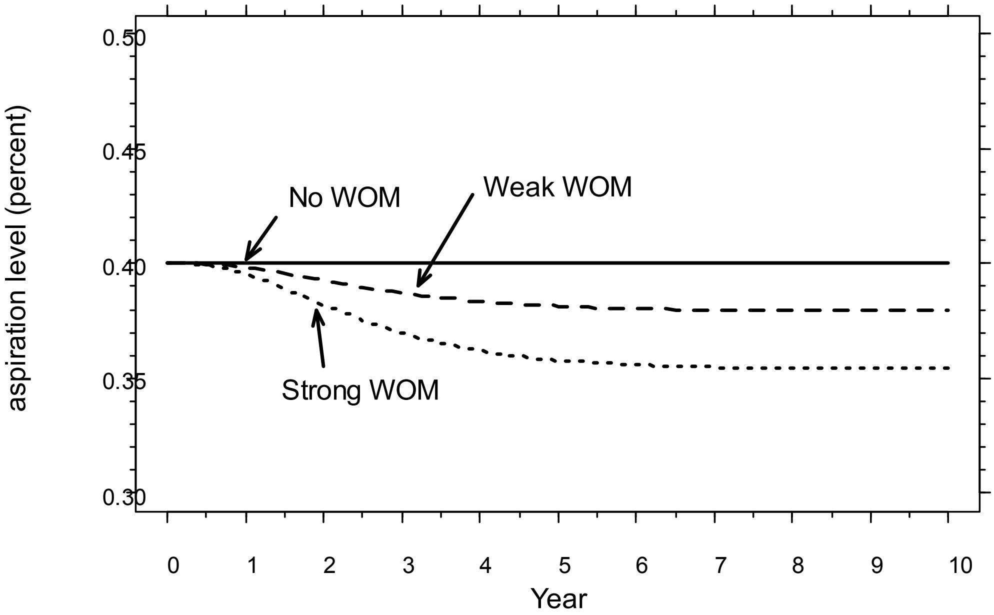

Figure 3-16: Development of aspiration level

The model can be used to develop new hypotheses that can be turned back to empirical researchers for further evaluation. For example, one could question the assumption that the aspiration level is influenced only by negative word-of-mouth and not by positive word-of-mouth. Inclusion of positive word-of-mouth (reflecting an increased expectation due to positive experiences) would decrease the *customer equity* in the third scenario slightly by -0.4% to $152.55M. On the other hand, if OSN such as Facebook lead to an average sharing of negative (positive) experiences with 10 (5) persons, the *customer equity* would be boosted by 5.2% to $161.08M – subject to the condition that the quality (i.e., trustworthiness) of word-of-mouth is not affected by their electronic submission. One could also argue that negative word-of-mouth is not only transmitted to more people but is also more strongly remembered. The resulting *customer equity* of $148.42M is indeed 3.1% lower, but it is still higher than the *customer equity* of the first scenario considered without word-of-mouth effects.

These examples show the importance of the integrated System Dynamics model in explaining the contradictory results of previous findings. This might stimulate further research based on hypotheses that can be derived from this model.

3.2.3.4 Critical Reflections and Limitations

The integrated approach of the model helps decision makers to better understand the interrelationships at the macro level and concentrate on the right questions for strategic decisions. For instance, the simulation results suggest that the observed organizational practice to “devote far more resources, time, and attention to controlling negative WOM than they do promoting positive WOM” (Williams and Buttle 2011, p. 85) might be counterproductive from a value-based point of view. Even if several assumptions or parameter values of the presented simulation models are changed, the development of company value is positive. In a system assuming a comparatively high degree of dissatisfied customers (30% per period), with negative experiences shared with twice as many persons as positive experiences and negative word-of-mouth causing twice as strong attitude changes as positive word-of-mouth, the used measure (*customer equity*) still turns out to be higher than in a system without any word-of-mouth effects. This is due to different developments in the number of existing customers versus the number of prospects. Hence, the decision makers of companies who offer attention-prone goods or services could consider promoting the strengths of positive word-of-mouth instead of preventing negative word-of-mouth. Simulation results also show that a general increase in the number and strength of word-of-mouth results in an increase in company value. Given the initially described higher interconnectedness owing to OSN such as Facebook and new technologies, the companies offering attention-prone goods or services could in general benefit from increased word-of-mouth. However, no empirical studies could be found that support or negate this hypothesis.

Sections 3.2.1 to 3.2.3 contribute to research in two main ways. First, the presented model itself offers a way to generate new hypotheses by simulating the interplay of existing research findings using systems thinking. In addition to handing back the hypotheses to empirical researchers, the model can also be used to help decision makers focus on the most important areas through adequate selection of measures. This will be shown in the next section. Second, the meta approach is used to combine an analytical decision model, established theories, and empirical findings (see Figure 3-7). This idea can prove useful in other areas as well and help avoid the frequent issue of isolated studies resulting in potentially misleading insights. Neglecting system perspectives has been criticized earlier (Meadows 1980). The presented model aims at contributing to closing a gap in the scientific cycle of designing new theories and observing real-world behavior.

Admittedly, the presented model entails some limitations that might motivate further research. First, the model is based on a number of assumptions, theories, and empirical evidence. While they were selected on the basis of plausibility, general acceptance in research, and causal meaningfulness, the model and its simulation results cannot be regarded as final “truth” (Popper 2002). Consequently, simulated behavior should be seen not as accurate prediction but as a step towards a better understanding of the interplay of existing research findings with the objective to find and substantiate new hypotheses. Second, there have been discussions on whether acquisitions follow a concave downward or rather an s-shaped function (Simon and Arndt 1980). In this case, the more common one was chosen, thereby also avoiding additional complexity. The results would vary significantly depending on the inflexion point. If future research would add further insights, these effects or theories can and should be subjected to refinement. Third, each part of the model is based on averages. For example, in reality there will be some very active customers transmitting a lot of word-of-mouth while others do no tell anybody. However, this simplification seems reasonable, because the objective is to propose an integrated model to quantify the value-based implications of word-of-mouth effects. Thus, attention is not distracted to better understand the principle interplay of the various feedback loops in such a complex system.

The model could be extended to also include the consequences of word-of-mouth effects that have no clear indications in literature. For instance, both the stimulation cost and the dissatisfaction rate could be altered through the strength of word-of-mouth effects. Another area worth closer future study is the tradeoff for splitting retention spending between stimulating complaints and satisfying the complainants with complaint solutions.

3.2.4 Application of the I²RDM Method

This section applies the I²RDM method proposed in chapter 2 on the previously presented integrated System Dynamics model to simulate the economic implications of word-of-mouth effects. Compared to the first case (see section 3.1), this model is significantly larger in terms of parameters. Furthermore, the model's purpose is not optimization but simulation in order to better understand the impact of word-of-mouth effects. Subsequently, the procedure model of the I²RDM method (see Figure 2-1) is applied to identify the importance of measures and derive a prioritization.

Step A: Identify top key measure. As argued in section 3.1.4, a suitable top key measure is the CE. Following the value-based management approach, CE should be maximized (or a loss of CE minimized).

Step B: Delineate area of responsibility. The area of responsibility comprises that part of a business that is influenced by marketing efforts (and hence prone to word-of-mouth effects). Marketing analysts or marketing managers are decision makers that have to navigate within this field and may thus benefit from the model.

Step C: Model causal relationships. The causal model has been developed and described in section 3.2.3.2. The overall causal loop model is depicted in Figure 3-13.

Step D: Model stock and flow diagram. The stock and flow model has been developed and described in section 3.2.3.1. The overall stock and flow diagram is depicted in Figure 3-11.

Step E: Formulate simulation model. The simulation model has been developed and described in section 3.2.3.3. Differential equations, realistic parameters and initial conditions were defined for all model elements. The System Dynamics tool Vensim® DSS 5.9e has been used to model the required functions. In the insurance example, the equations were justified by previous research results and empirical observations. Typical parameter values have been adopted from Berger and Nasr-Bechwati (2001) and were used to instantiate the model. Due to conflicting empirical results, word-of-mouth effects have been added using two different scenarios and a base case without word-of-mouth effects.

Step F: Validate simulation model. Prior to interpreting results, the model's validity has been examined. While the model passes structure tests (as dimensional consistency checks) and structure-oriented behavior tests (as feasible model behavior in case of applying extreme values), a behavior pattern test (as matching model predictions with the observed reality) or an empirical confirmation are not available.

Step G: Prioritize measures based on sensitivity analysis. In order to determine the importance of measures, the effect of a parameter change of +/–10% on the top key measure CE is simulated. Figure 3-17 shows the results of this numerical sensitivity analysis for one stock (*Prospects*) and most converter elements (except for word-of-mouth-related converters since the resulting change of CE was less than 0.5% for all of them).

The remaining stock elements are required in the model but start empty (i.e., with the value "0") and are hence not relevant. Valve elements and converter elements purely calculated from other converters are excluded. The reason is that in this case a change of +/–10% may be caused by different variations of upstream model elements (see section 3.1.4 for further justifications of this simplification). Since the numerical sensitivity analysis adopts a ceteris paribus approach, the analytically calculated optimal split (see section 3.2.3.3) between retention and acquisition spending has not been recalculated after a parameter change.

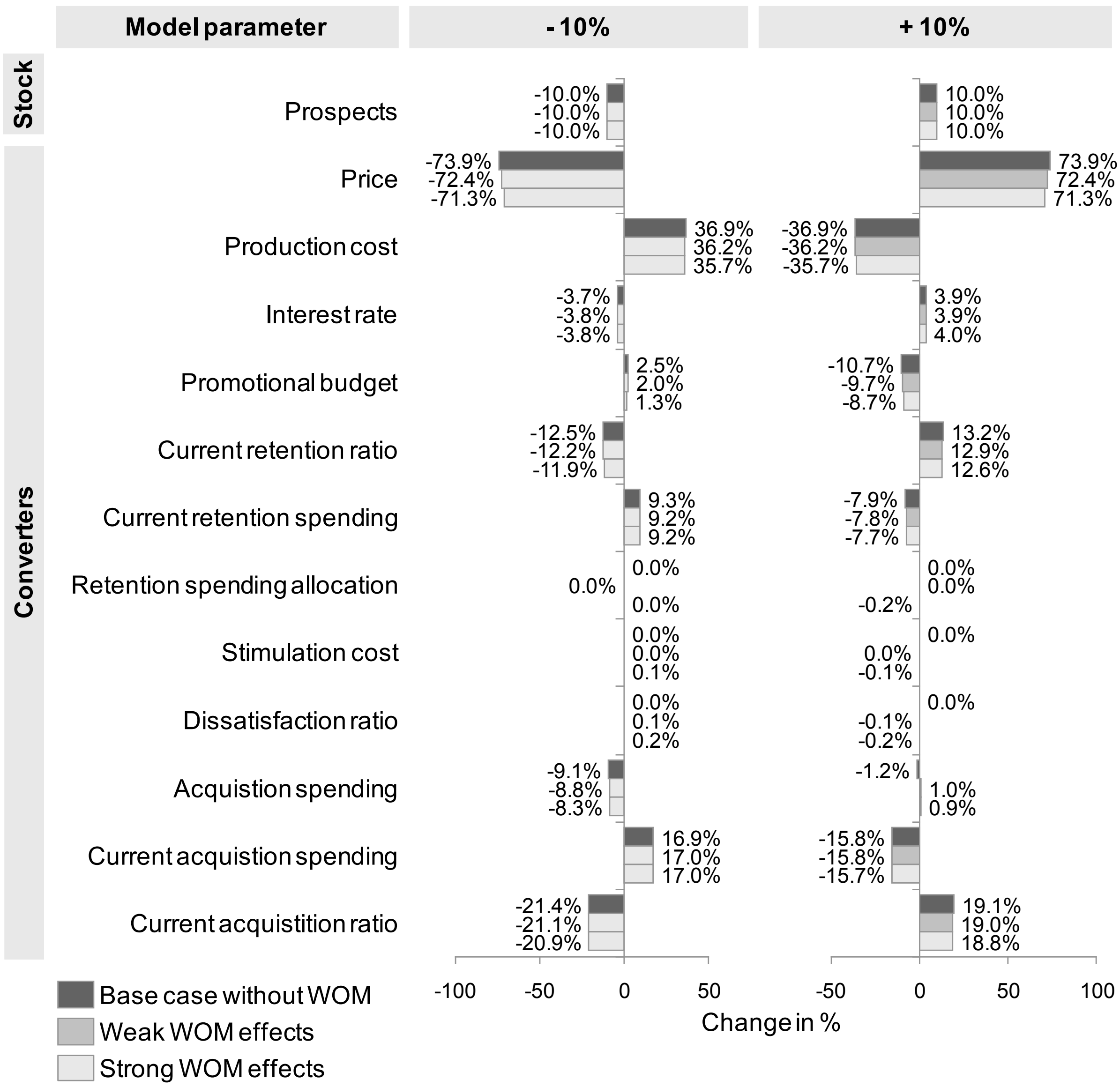

Figure 3-17: Numerical sensitivity analysis of the System Dynamics model for word-of-mouth effects

As can be seen in Figure 3-17, the results vary only marginally between the three scenarios. The sensitivity analysis of the parameter *acquisition spending* in the base case without word-of-mouth effects confirms the analytically calculated optimum: A change of this parameter inevitably reduces CE (by 9.1% in case of a reduction of 10% and by 1.2% in case of an increase of 10%). Furthermore, due to equations (11) and (12) it is logical that a change of both *current retention ratio* and *current acquisition ratio* stronger influences the CE than a change of *current retention spending* or *current acquisition spending*. A rather surprising result of the sensitivity analysis is the stabilizing effect of stronger word-of-mouth. As can be seen from Figure 3-17, the change of CE is smaller in the scenario with weak word-of-mouth effects and smallest in the scenario with strong word-of-mouth effects. The only exceptions are the *interest rate* and word-of-mouth-related measures not depicted in Figure 3-17. The latter can be explained since a percentage-based constant change has stronger effects for stronger word-of-mouth (e.g., 7.7 compared to 3.3 average *persons approached by defecting customers* in case of a 10% increase). The observed (small) effect that the *positive decay rate* has a stronger influence than the *negative decay rate* is reasonable against the background discussed in section 3.2.3.3, namely that word-of-mouth in principle has a positive effect.

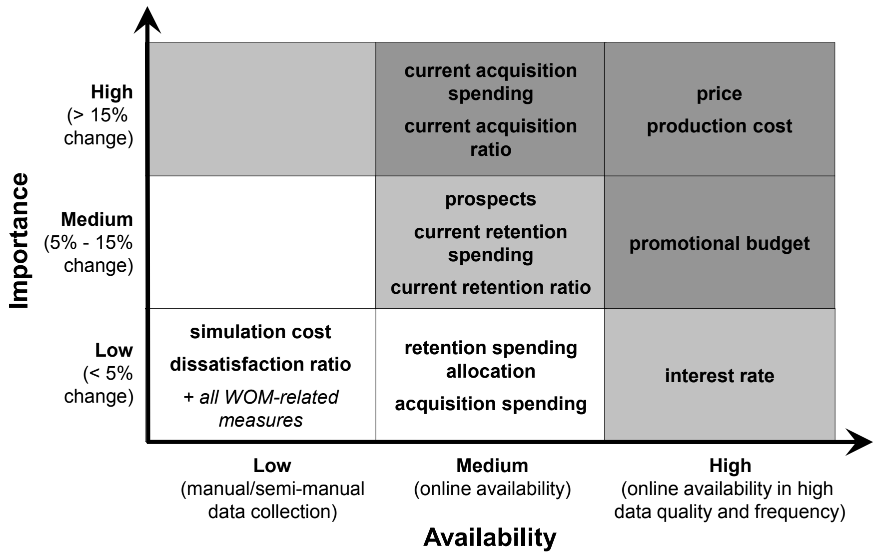

Figure 3-18: Resulting prioritization matrix of the System Dynamics model for word-of-mouth effects

For prioritization purposes, as in the first case of application, three classes are distinguished: under-proportional (less than 5% change), about proportional (between 5% and 15% change), and over-proportional (more than 15% change) influences on the top key measure. Data availability is selected as second dimension and split into three classes: low (manual or semi-manual data collection), middle (online availability), and high (online availability in high data quality and frequency).

In the second case of application, it is assumed that the company slightly changes the prioritization matrix introduced in section 3.1.4: Importance and availability are valued equally. Figure 3-18 shows the resulting matrix for the measures of the model.

In this second case of application, all measures with a high importance also have a rather high availability. The importance of *price*, *production cost* and number of *prospects* (which due to the model structure – that starts with no customers and complainants – should also include information on the number of *customers* and *complainants* that only emerge over time) for the development of the CE are not surprising. Neither are the other financial measures referring to *acquisition/retention spending* or their ratios. Surprising is the comparatively minor impact of changes in the word-of-mouth-related measures (such as *persons approached by exiting customers* or *negative decay rate*) and measures for complaint management (*simulation cost*, *dissatisfaction ratio*, and *retention spending allocation*).

3.3 System Dynamics Model for Non-Renewable Resources[9]

In dynamic business contexts where knowledge is continually evolving and thus critical for better organizational performance, not only knowledge re-use but also knowledge re-creation becomes more and more important. One of these contexts is the use of non-renewable resources in innovative high-tech products. Since media recently spread – often contradictory – news about the increasing scarcity of non-renewable resources, decision makers face a high degree of uncertainty. They struggle to understand and handle the information available. Therefore, it is essential to provide a methodological approach to externalize and combine expert knowledge of a system's inherent logic. Hence, in this section is shown how mental models of experts can be transformed into an explicit simulation model in order to support decision makers comprehending the short- and long-term dynamic interdependencies of the development of non-renewable resources on demand, supply, and price. For this purpose, known cause-and-effect relationships are combined into an integrated model using the System Dynamics methodology. The application of the idea to capture knowledge in a simulation model is exemplarily instantiated with real-world information for the case of indium.

After motivating the business demand in section 3.3.1, section 3.3.2 gives an overview of related work of the theoretical background. Then, both structure (section 3.3.3.1) and behaviour (section 3.3.3.2) of the model are presented. Afterwards, the model is exemplarily applied to the non-renewable resource indium (section 3.3.3.3). Section 3.3.3.4 critically reflects on key findings, discusses limitations, and points out future research. Finally, the proposed I²RDM method for information requirements analysis is applied in section 3.3.4.

9 Sections 3.3.1 to 3.3.3 were written in collaboration with Benedikt Gleich (FIM Research Center) and Dr. Dieter Reinwald (FIM Research Center) and are, except for marginal changes in details, identical with Gleich et al. (2011).

3.3.1 Business Demand

Knowledge management has been defined as uncovering and managing different levels of knowledge from individuals, teams, and organizations in order to improve performance (Davenport et al. 1998; Nonaka 1994). Especially in dynamic business contexts where knowledge is rapidly evolving, not only re-use but also re-creation of knowledge – that is, the continual refresh of the knowledge base (Apostolou and Mentzas 2003) – represents a substantial source of long-term competitive advantage. One particular dynamic context is the use of non-renewable resources in production companies. Since certain metals, rare earths and other non-renewable resources form an essential fundament for innovative high-tech products, their increasing scarcity recently became more and more important (European Commission 2010). This can have significant impact on decisions to be made and thus on the sustainable success of the organization.

If, for instance, a research & development department needs to decide to what extent a certain non-renewable resource will be used in a new product, this design decision has far-reaching consequences for the whole life of the product. Potential subsequent design changes are not only time-consuming but can also turn out to be very expensive. For an adequate decision a comprehensive and evolving knowledge base is required. However, this is often challenging. Even though experts working in research & development get – often contradictory – pieces of information from internal (such as the strategy department) and external (such as the media) sources, it is difficult not only to externalize and combine these new insights but also to re-create knowledge in order to address questions as:

- How to judge short-term and long-term consequences of a sudden significant supply drop (or increase) of a particular non-renewable resource? For example, latest news reports that China – accountable for 97% of the world's rare earths production (European Commission 2010) – plans to reduce its exports of rare earths by up to 30% (Bradsher 2010).
- To what extent would the existence of an appropriate substitute material impact the total demand of a particular non-renewable resource? Tantal – currently used in micro-capacitors – could be substituted by the explorative non-ferroelectric material $CaCu_3Ti_4O_{12}$ due to its immense advance in quality (Lunkenheimer et al. 2010).
- How does the price influence recyclability for a particular non-renewable resource? Even though indium – a rare metal – is not recycled so far, the USGS yearbook (Tolcin 2009, p. 35.1) states that "recent improvements to the

process technology have made indium recovery from tailings feasible when the price of indium is high".

Although such isolated influencing factors can be understood quite easily, their combined occurrence can result in shortcomings: Misperceptions of feedback, unscientific reasoning, judgmental biases, and defensive routines (Sterman 2000; Wolstenholme 2003) hinder a decision maker's ability to comprehend the structure and dynamics of complex systems. These difficulties are intimately connected with problems in the mental model (i.e., "conceptual representations of the structure of an external system used by people to describe, explain, and predict a system's behavior" (Capelo and Dias 2009, p. 1)) of the decision maker. In order to improve the individual mental model, it is necessary to externalize the knowledge of the decision maker and combine it with the knowledge of experts in the organizational domain. Since these mental models have been central to System Dynamics from the beginning of the field (Sterman 2000; Wolstenholme 2003), this methodological approach has been claimed to be able to manage and apply knowledge for better organizational decision making (Forrester 1961; Senge 1994).

Because literature also shows the acceptability of System Dynamics for analyzing time-continuous, short-term and long-term developments, and feedback loops, the next sections introduce a System Dynamics model for the development of a particular non-renewable resource in order to support decision makers understanding the short- and long-term effects of resource depletion and resource recycling on demand, supply, and price. Thereby, the System Dynamics model is used to capture knowledge.

3.3.2 Theoretical Background

The discussion about the scarcity of non-renewable resources is a long-known and recurring topic. Already 80 years ago, Harold Hotelling referred to their rapid and unsustainable exploitation (Hotelling 1931). This view was quantified by Meadows at al. (1972; 2004) in the controversially discussed Club of Rome study "Limits to Growth" claiming the exhaustion of reserves of many non-renewable resources within the next few decades. Since then literature has discussed and contributed to this field from various perspectives. In order to structure theoretical findings and related work on different aspects of non-renewable resources, subsequently the three domains mining, market, and usage & recycling are distinguished (see Figure 3-19).

First, the mining domain contains related work regarding how non-renewable resources are made available through exploration efforts and subsequent exploitation. Tilton (2002) defines non-renewable resources as "mineral resources" which are finite since the world is finite. Hence, if demand persists, depletion will be ineluctably at some point in the future (in literature this position is known as "fixed stock paradigm" (Tilton 1996)). This point was first simply calculated by dividing the current reserves by the annual demand for production (reserves-to-production ratio). But following this logic, many resources (such as tin) would already have been exhausted (Meadows et al. 1972). Although the world's finiteness cannot be denied, due to the huge abundance of non-renewable resources in the earth's crust, geological availability is not a critical issue (European Commission 2010; Tilton 2009). In contrast to the widespread apprehension of non-renewable resources' depletion, there are arguments that mining can keep up with the future rising demands (Tilton 2009).

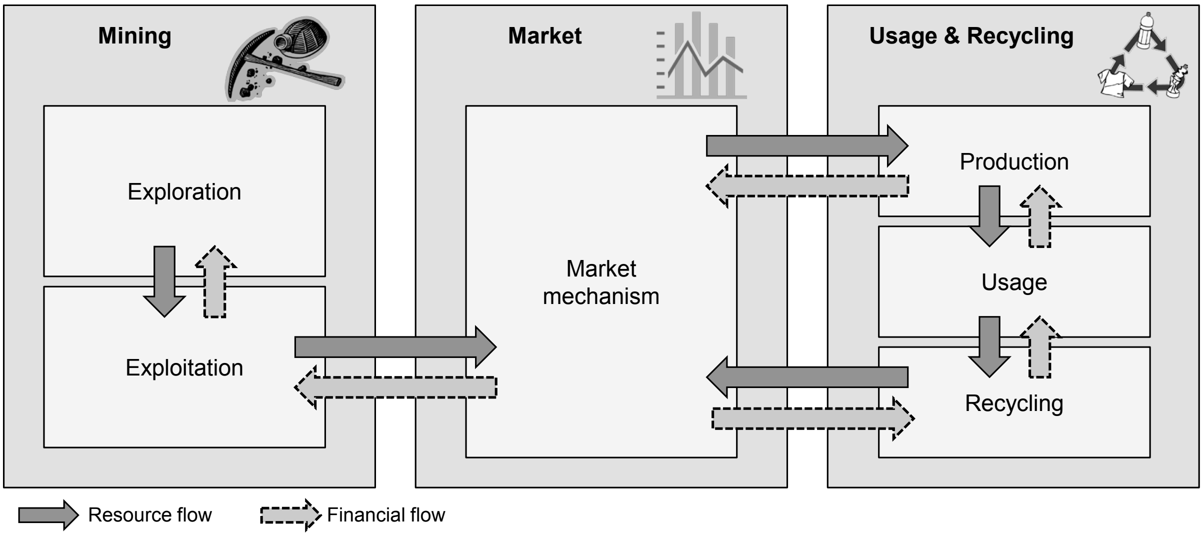

Figure 3-19: Domains and their relationships structuring the System Dynamics model for non-renewable resources

Work of the second domain (the market perspective) examines how discrepancies between supply and demand are balanced through price adjustments. According to Tilton (2009, p. 5), economic depletion is a more critical issue than physical depletion and would "occur gradually over time as the real prices of mineral commodities rise persistently". So, scarcity of non-renewable resources is seen as an economic problem (a position known as opportunity cost paradigm (Tilton 1996)). On the one hand, it is expected that the demand for most non-renewable resources will continue to increase in the future (European Commission 2010). In addition, exploitation costs may rise and demand can be met by supply only with delays (According to Hartman and Mutmansky (2002) a new mine can only be exploited after 5 to 13 years and requires multi-million investments). Modeling future developments should also take into account lower ore quality of non-renewable resource deposits as the rate of exploitable resources in a mine's ores decreases (Krautkraemer 1998). On the other hand, new technological findings and recycling might compensate these cost-increasing effects. In fact, over the last decades many metals have actually declined in price (Radetzki 2008; Svedberg and Tilton 2006). Nevertheless, it remains an open question to what extent the empirically observed quality decrease of ore grade of future explorations is offset (or even overcompensated as Tilton (2009) suggests) by technological advances driving down exploitation cost (van Vuuren et al. 1999).

The third domain deals with the usage of non-renewable resources to manufacture products and their recycling (if applicable) after use. Unlike many other substances, most non-renewable resources as metals will not be physically consumed. Instead, they can be used an infinite number of times. However, as of today many valuable non-renewable resources are lost due to dissipation and shortcomings of recycling. Reasons include non-economic recycling costs, lacking recycling facilities or dissipative usage, as in the case of zinc as corrosion protection (Plachy 2004). The question to what extent non-renewable resources can be recycled depends on the field of application. For instance, indium is difficult to recycle due to its low concentration in typical indium containing products like liquid crystal displays (LCDs) (Tolcin 2009). In contrast, the vast majority of copper, for instance contained in cables or pipes, can be recycled more easily (Goonan 2010). Thus, for each product and each application, there is a ratio of factual recycling, a ratio of technically possible recycling and a ratio of economically feasible recycling. In addition, other approaches like re-use and remanufacturing can improve the usage of non-renewable resources, as for instance LCD are fit for re-use or remanufacturing in many cases.

3.3.3 System Dynamics Model

Subsequently, a System Dynamics simulation model is presented that formalizes knowledge of structure and behavior of non-renewable resources' use. Thereby, it takes the perspective of a production company that needs a non-renewable resource to manufacture one or more of its products. The model separates knowledge about system structure and behavior from the information required to instantiate the system. This shall help reevaluating the situation once new information becomes available. Scenarios can be built to capture knowledge about possible price ranges as well as demand and supply developments depending on defined assumptions. While admittedly the assumptions themselves represent simplifications of the real world, a coherent company-wide set of assumptions defined by experts (e.g., from strategy department) is expected to outperform the various individual interpretations.

The proposed model draws from several approaches. The most important elements are: Opportunity cost paradigm (future demand estimations fail to incorporate future demand changes due to the price elasticity of demand), two kinds of resource sources, namely primary (mining) and secondary (recycling), and the pricing strategy of producers (mining and recycling companies will adjust their profit margin based on factors as, for instance, the supply-demand ratio).

While there are many effects worth considering, the focus is laid on a set of accepted and crucial elements to keep the model comprehensible. Most simplifying assumptions made can be subsequently relaxed through small changes to the model (e.g. by adding new feedback loops to incorporate other price-influencing factors) or the use of more intricate mathematical distributions. A wide range of distributions is supported by the simulation software used (Vensim® DSS 5.9e).

3.3.3.1 Model Structure

Figure 3-20 shows the simulation model. The general model logic draws from findings of van Vuuren et al. (1999) with two additions. At first, a company perspective is adopted with a focus on decision support for the use of non-renewable resources. Second, the possibility to dynamically incorporate information changes is added. By means of scenarios knowledge can be communicated within a company. To point out how to use System Dynamics for these objectives, the core concepts (represented by *italicized* words) are delineated below. The stock *Reserves* represents the current amount of reserves made available by mining companies for the production industry. Based on empirical evidence from historical data (European Commission 2010) reserves are expected to increase in future due to new findings. This increase of non-renewable resources is indicated by the inflow *material exploration*.

On the other hand, reserves will decrease – modeled as flow variable *material to mine* – based on those resources required by the production industry in order to satisfy the demand. The *demand* is based on the variable *predicted demand* as of now via a Gompertz function (Boudreau et al. 2009), but also dynamically adjusted to price changes. The stock *Supply* contains the total amount of non-renewable resources available to the production process. It is reduced by the flow variable *material usage*, that is, resources used in the production process (represented by the stock *Production*). At this stage, resources are processed into products for consumers. The rate of material wasted in the production process step is calculated by means of the constant *average ratio of new scrap during production*. In this model, the total amount of new scrap material is assumed to be able to be recovered and thus reintegrated into the production lifecycle (represented by the flow variable *new scrap*). The other part of the material will be used for production. The amount of sold products is modeled by the flow variable *consumption*.

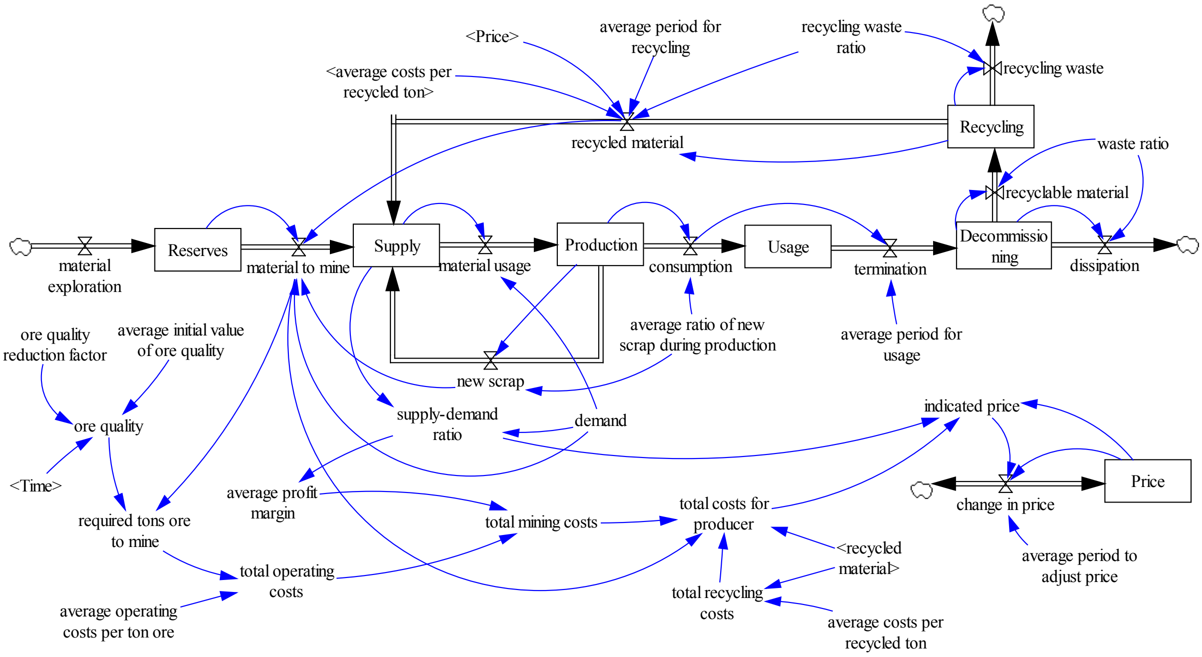

Figure 3-20: Stock and flow diagram of the System Dynamics model for non-renewable resources

The stock *Usage* represents the potentially long-standing utilization of non-renewable resources during the use of products by consumers. The average usage duration is determined as the constant *average period for usage*. After the expected product lifetime (represented by the flow variable *termination*), in the stock *Decommissioning* the dumped products are classified according to their recyclability, represented by the constant *waste ratio.* If the dumped products are not recyclable (i.e., waste ratio = 1), the products will be totally dissipated (represented by the flow variable *dissipation*). In contrast, if the products are (partly) recyclable (i.e., 0 ≤ waste ratio < 1) they will be classified as *recyclable material*. This kind of material is collected in the stock *Recycling*. If the *average costs per recycled ton* are higher than the price (both variables are illustrated as shadow variables in angle brackets) for newly mined material, no material will be recycled since it is more profitable to purchase newly mined non-renewable resources. Otherwise, if the costs for recycling are lower than the price, recycling will become economically attractive and material will actually be recycled. In this case, a certain fraction (represented by the constant *recycling waste ratio*) of the recyclable material cannot be recovered during the recycling process which is visualized by the flow variable *recycling waste*. The rest of the non-renewable resource flows back as *recycled material* into supply considering the *average period for recycling*, that is, the delay caused by the recycling process itself.

In order to investigate the consequences of discrepancies in supply and demand, the stock *Price* representing the (fundamental) market price of the non-renewable resource is integrated. Considering the delay *average period to adjust price,* this stock will be changed (represented by the flow variable *change in price*) based on the difference between price and indicated price. The latter represents the target price that will be reached with the defined delay. It is calculated as follows:

$$indicated\ price = MAX\left(\frac{Price}{supply-demand\ ratio}, total\ costs\ for\ producer\right) \qquad (17)$$

Here, the *supply-demand ratio* calculates the proportion of supply and demand. If supply is lower than demand, the indicated price will increase. Otherwise, the indicated price will decrease. The *total costs for producer* per ton of the non-renewable resource are assumed as minimum for the indicated price in order to guarantee a long-term cost-effective exploitation for mining companies. These total costs are defined as the weighted average of the *total recycling costs* and the *total mining costs*. The first results from the multiplication of the recycled material by the average costs per recycled ton, whereas the second is calculated by the *average profit margin* (modeled as graphical function depending on supply-demand ratio) multiplied by the *total operating costs*. To determine these operating costs, the constant *average operating costs per ton ore* need to be multiplied by the *required tons ore to mine*. The latter variable is the amount of ore needed to gain the required tons of the non-renewable resource. Since the quality of deposits tends to decrease because better mines are exploited first, the *ore quality* needs to be incorporated. This variable, also known as ore grade, stands for the concentration of a non-renewable resource in the ore of a deposit, e.g. in parts per million (ppm) (Hartman and Mutmansky 2002). The more ore is exhausted, the lower the concentration gets. For this reason, it becomes more intricate and expensive to extract the non-renewable resource. The model applies an exponential decay function to calculate the ore quality which depends on the constant *average initial value of ore quality*, the temporal factor *Time*, and the *ore quality reduction factor*. This ore quality reduction factor determines the slope of the ore quality change: the lower the factor, the faster the ore quality decreases.

3.3.3.2 Model Behavior

The model behavior arises from its structure integrating dynamic complexity through overlapping short-term and long-term effects. In order to improve the mental model of a decision maker it is necessary to examine the essential feedback loops. The fundamental modes of feedback loops are exponential growth, goal seeking, oscillation, and interactions of these (for further detail, see Sterman (2000) and Wolstenholme

(2003)). Since the model contains various feedback loops, subsequently only the pivotal ones are examined which integrate the key factors demand, supply, and price. On this account, an isolated perspective on both the cause and the effect variable is taken (i.e., a ceteris paribus consideration is applied).

First, two essential feedback loops for the demand and its impact on costs and mining are examined: the *demand-profit margin loop* and the *demand-material loop*. For the former loop the implicit assumption is that the lower the supply-demand-ratio is, the higher the average profit margin will be that the mining companies can claim. It raises the total costs the production company has to pay. This results in an increase of the indicated price and, in turn, reduces the demand at last. Therefore, the demand-profit margin loop is characterized by a goal seeking behavior. In the latter loop a higher demand leads to a higher amount of material to mine. Due to the decreasing ore quality over time, more tons ore are required to satisfy the demand. This effect increases the total operating costs and, again, the total costs for the production company. Through the increase of the price, the demand will reduce. This is a goal seeking loop, too.

The main feedback loops for supply are named *supply-recycling loop* and *supply-price loop*. The former determines the transition of a non-renewable resource from supply across production, usage, decommissioning and recycling back to supply. The assumed s-shaped growth of this loop results from an exponential growth which then gradually slows until the state of the system reaches the equilibrium level, that is, the demand in this case. This behavior is based on an overlap of the two fundamental modes exponential growth and goal seeking in the underlying model structure. The latter loop examines the impact of supply on the price for the non-renewable resource. Through a raise in the supply the supply-demand ratio increases. This leads to reductions of the indicated price and, in turn, the price. A lower price drives demand which finally increases supply. Hence, the behavior of the loop is exponential growth.

Finally, the main feedback effects in terms of price are investigated. Considering the *price-recycling loop*, an increase of the price will also lead to a raise in the amount of recycled material (conditionally to the technical possibility of recycling) if the costs for recycling fall below the price for mining new non-renewable resources. The recycled material will increase the supply, thus reducing the indicated price and the price at last. Therefore, this loop demonstrates a goal seeking behavior.

Since model structure and model behavior are determined, in the following section the model is exemplarily applied for the non-renewable resource indium. Based on comprehensible assumptions and facts from literature three scenarios are established in order to demonstrate both the model's applicability in principle and the effects on the key variables demand, supply, and price.

3.3.3.3 Simulation and Scenario Analysis

Since the mid of 1980s – when indium started to gain economic relevance – both annual consumption and price have multiplied tenfold (USGS 2007). The upward trend is expected to continue. The European Commission (2010) assumes indium demand to triple until 2030 due to its importance for the production of LCDs, touch panels, and thin film solar cells.

But while the occurrence of former demand and supply predictions would have resulted in faster-growing depletion of indium and higher market prices, despite growing demand indium prices have declined compared to their high four years ago (USGS 2007). While the observed relaxation has mainly been attributed to new explorations, this is not the only factor expected to play a pivotal role in the future:

- *New explorations*. In 2007, China corrected its indium reserves from 280 to 8,000 tons (USGS 2007; USGS 2008).
- *Delayed reactions*. In case of scarcity of indium, other mines could – with some delay – take over production since indium is produced as a by-product of other non-renewable resources as lead, zinc, copper, tin and silver (Mikolajczak 2009).
- *Recycling*. While indium "lost" during the production process is already reclaimed, recycling from end products as LCDs is currently not economically feasible (Mikolajczak 2009).
- *Substitution*. For most applications of indium, substitution candidates have been found. But their commercial feasibility is not always given – and if so, a delay of some years is involved (USGS 2010).

These factors and their interconnectedness increase the risk for decision makers to misjudge the situation due to partial or improper knowledge. To determine the probable range of future demand, supply and price developments, subsequently three scenarios are defined and simulated – a base case, a pessimistic case and an optimistic case – covering a wide range of assumptions currently found in real-world discussions.

Scenario Description

The input parameters for the scenarios originate from literature as geological studies, reports of mining engineering companies, and long-term socio-economic forecasts.

Knowledge about the solution space can be communicated to decision makers by means of different scenarios. Since the model's behavior is set to adjust supply to demand (conditionally to sufficient reserves or recycling capacity), the scenarios concentrate on five variables that drive either demand or influence the supply capacity. The former can be influenced directly (through different assumptions for the *predicted demand* in 2030) or indirectly (since a change in *ore quality* drives production cost as lower boundary for the price which in turn alters demand due to its elasticity). The latter can be divided into a primary supply capacity (depending on known and newly discovered reserves) and a secondary supply capacity (depending on feasibility of recycling). The supply capacity is characterized through the three variables *initial value of reserves*, *material exploration* and *waste ratio.* Table 3-8 gives an overview of both variables and their respective scenario instantiations.

Table 3-8: Input parameters for the scenarios

Variable	Description	Base case	Pessimistic case	Optimistic case
predicted demand	Expected demand of indium in 2030 [in tons per year]	2,000	5,000	500
material exploration	Expected explorations of new indium deposits [in tons per year]	1,000	500	1,000
initial value of reserves	Expected initial reserves of indium [in tons]	11,000	7,000	64,000
waste ratio	Share of not recyclable indium in products [in %]	90%	100%	60%
waste ratio	Time to reach technical feasibility of recycling [in years]	10	20	5
ore quality	Average quality change of indium ore concentrates during the simulation [in ppm → ppm]	100 → 80	100 → 50	100 → 140

While the base case has been designed with values currently assumed to have the highest probability, both other cases provide lower and upper boundaries in order to take into account potential pessimistic and optimistic developments. In a company, these scenarios and values would need to be defined by experts, for instance, from the strategy department.

The *predicted demand* forecast of 2,000 tons per annum in 2030 is seen as the most probable value and is based on an extensive study incorporating multiple forecasts for key technologies (Angerer et al. 2009). In an pessimistic case, new technologies could lead to an increased demand of up to 5,000 tons, for instance in case of further growing demand for thin film solar cells. On the other hand, more efficient technologies could lower the demand of newly mined indium to about 500 tons per year (Mikolajczak 2009).

The amount of new indium deposits – represented by the *material exploration* variable – is subject to controversial discussions. Basically, indium is about as frequent as silver and by these means not very rare (Jorgenson and George 2005; USGS 2010). Empirical evidence shows that the so-called static life time of reserve base for indium was in 2007 higher than in 1989 (European Commission 2010). New explorations can explain this phenomenon. Hence, a yearly material exploration rate of 1,000 tons is assumed for both base and optimistic case but a lower rate of 500 tons for the pessimistic case.

Furthermore, not only the increase of reserves but also the *initial value of reserves* could affect the system's behavior. While today there are known reserves of 11,000 tons (USGS 2008), Mikolajczak (2009) claims that much more indium can be found. Hence, for the optimistic case reserves of 64,000 tons are assumed. In the pessimistic case expert estimations are feared to be overly optimistic. Hence, the current reserves are reduced to 7,000 tons.

Currently, up to 70% of indium is wasted during the manufacturing process (new scrap) but can be regained within 30 days (Mikolajczak 2009). However, the indium contained in end products is not recycled so far. For the pessimistic case this situation is assumed to remain unchanged for the next 20 years (i.e., the *waste ratio* remains at 100%). In the base case recycling becomes technically feasible for up to 10% of indium contained in end products after ten years. Optimistically, the recycling ratio can increase to 40% within the next five years. The latter two cases only represent assumptions about technical feasibility – economic feasibility is inherent to the models behavior due to its price dependency.

The *ore quality* of indium deposits is a key factor for cost and price developments. Since indium is a by-product of ores containing other metals, it is difficult to apply the idea to presume a general ore quality decline as described by van Vuuren et al. (1999). Rather, indium ore quality depends on the underlying ore concentrate. Currently, mining is economically feasible for concentrates containing as little as 100 ppm of indium (Mikolajczak 2009). In the base case this is assumed to decrease to 80 ppm. On the other hand, there are mines like the recently closed Toyoha mine in Japan with an indium concentration of about 140 ppm (Jorgenson and George 2005). Hence, this value is set as an upper boundary in the optimistic case arguing that higher and relatively new exploration efforts will result in higher concentrations to be found. On the other hand, high quality deposits could be exhausted sooner than expected leading to a lower ore quality of 50 ppm – the average content of indium in zinc deposits (USGS 2010).

In summary, the five variables constituting the three scenarios represent a wide range of facts and plausible assumptions thereby allowing reasonable simulations.

Simulation Results

Based on the input parameters described above, simulation runs for each of the three scenarios have been executed.

In the base case, the price steadily rises from $500 per kilogram (kg) indium in 2010 to $749 in 2030 following an s-shaped growth. This equals a yearly average price-increase-rate of about 2%. While one could expect higher prices due to increasing demand, this is counteracted by a rather moderate increase of mining costs and the exploration of new resources. On the other hand, new substitution technologies and favorable exploration of new deposits could reduce the demand and increase ore quality. This has been simulated in the optimistic case. Here, the price gradually reduces to $100 per kg, converging at mining costs that decrease due to higher grade indium deposits. Lastly, there is the possibility of a combination of multiple unfavorable developments. Strongly increasing demand combined with a serious reduction of ore quality can lead to an extreme price increase. In the pessimistic case, the price triples to more than $1,500 per kg, equaling more than ten times the price of 2000.

As a rather surprising result, the new scrap rate turned out to be an important element for the price development. Since up to 70% of indium used in LCD production is first lost and then recycled (Mikolajczak 2009), this implies that large amounts of indium are circulating in production facilities. Here, decreases in the new scrap rate result in a price increase by a factor of two, making the new scrap rate on major price determinant. This effect can be explained through the stabilizing effects of new scrap on supply. Additional simulations also demonstrated that recycling can provide an upper boundary for indium prices – although costs for recycling are too high to provide an economically feasible alternative in the presented cases.

Altogether, besides a number of rather expectable findings, the simulation produced some surprising results, demonstrating the ability of System Dynamics to capture complex knowledge. Large amounts of previously incoherent information could be combined in a meaningful way, contributing to the re-creation of knowledge from plausible assumptions and formerly disconnected facts. In particular, scenarios help to communicate knowledge regarding possible variants of future developments of demand, supply and price.

3.3.3.4 Critical Reflections and Limitations

Admittedly, the presented System Dynamics model is beset with shortcomings and limitations that need to be addressed in future research endeavors:

- First, a company-wide consistent view does neither necessarily improve decision quality nor ensures a better understanding of a system's structure and behavior.
- Second, the level of detail of the presented model could be questioned. To gain a more holistic view in terms of recycling, the concepts of re-use and remanufacturing could be integrated as well.
- Third, while knowledge about fundamental market structures and dynamics is considered, other factors a decision maker needs to keep in mind are not modeled. For example, the price for a non-renewable resource not only results from fundamental economic developments but also from factors as speculation. While there are System Dynamics-based approaches to capture such factors as well, the required assumptions would stem from "gazing into crystal balls" rather than be based on facts.
- Fourth, even though the model is based on findings from literature to approximate system behavior, an empirical validation based on past data is missing. Therefore, it would be insightful and strengthen the evaluation to conduct additional studies.

Nevertheless, the proposed model demonstrates how System Dynamics models can be used to capture implicit knowledge of a system's structure and behavior thereby improving knowledge-based decision support. A set of expert beliefs (formalized as assumptions) and facts can be shared and aligned company-wide in order to contribute to a coherent knowledge base. This is especially important in fields that are controversially discussed and require a continually re-use and re-creation of knowledge as e.g. the demand, supply, and price developments of non-renewable resources.

3.3.4 Application of the I²RDM Method

This section applies the I²RDM method proposed in chapter 2 to the previously presented System Dynamics model to capture knowledge on non-renewable resources. Compared to the first two cases of application (see sections 3.1 and 3.2), this model lacks an obvious top key measure such as the CE. Furthermore, the model's purpose is not optimization but the use of System Dynamics for knowledge management. Subsequently, the procedure model of the I²RDM method (see Figure 2-1) is applied to identify the importance of measures and derive a prioritization.

Step A: Identify top key measure. The model's purpose is to help decision makers with their decision regarding the use of a specific non-renewable resource. Knowledge on factors influencing the price is combined to predict possible price developments. Hence, the central key measure is the *price*. All remaining measures will thus be judged based on their influence on the price.

Step B: Delineate area of responsibility. The product development department decides on the design of a new product. Already during design time, a big share of a product's lifecycle costs is build-in. The area of responsibility comprises that part of a business that is influenced by price changes of raw materials as non-renewable resources. Product developers, product managers and procurement managers are decision makers that may benefit from the model.

Step C: Model causal relationships. Decision makers and business analysts jointly need to identify causal relationships. Figure 3-21 shows the causal loop model that corresponds with the presented stock and flow diagram (see section 3.3.3.1). Note that only the five main causal loops described in section 3.3.3.2 are depicted.

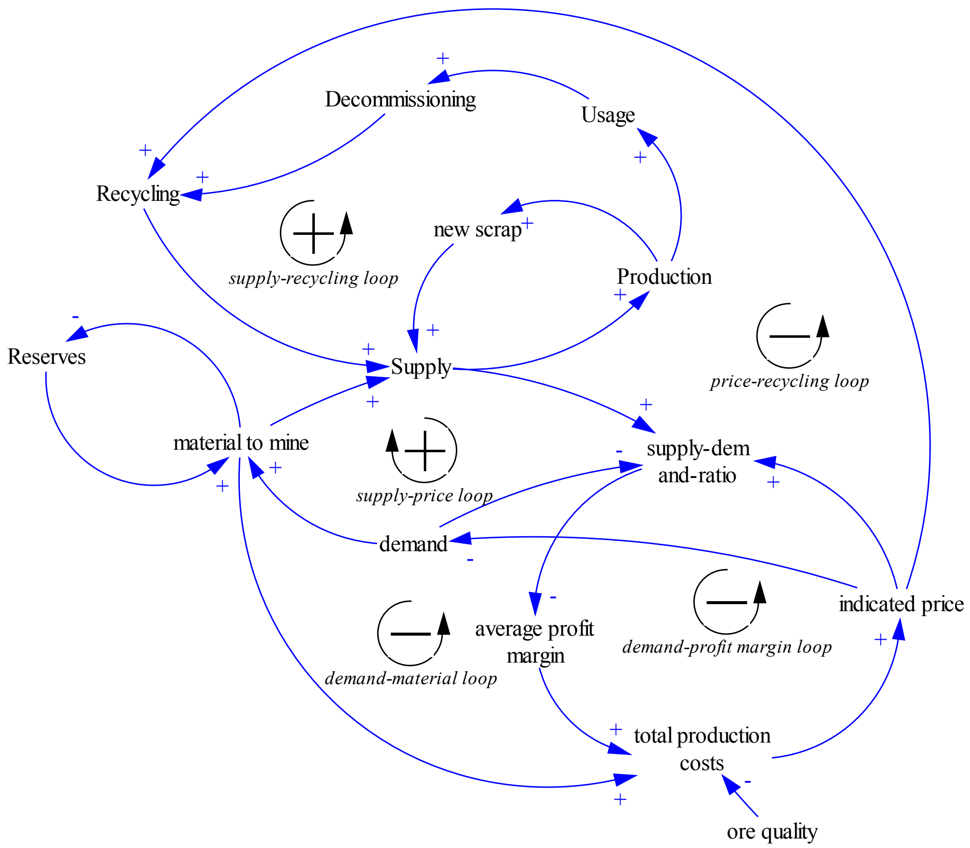

Figure 3-21: Causal loop diagram of the System Dynamics model for non-renewable resources

Step D: Model stock and flow diagram. The stock and flow model has been developed and described in section 3.3.3.1. It is depicted in Figure 3-20.

Step E: Formulate simulation model. The simulation model has been developed and described in section 3.3.3.1. Differential equations, realistic parameters and initial conditions were defined for all model elements. The System Dynamics tool Vensim® DSS 5.9e has been used to model the required functions. For the example of indium, the equations were justified by empirical studies and official data. Due to the lack of confirmed data for certain parameter values, three scenarios have been developed and used to instantiate the model (see section 3.3.3.3).

Step F: Validate simulation model. Prior to interpreting results, the model's validity has been examined. While the model passes structure tests (as dimensional consistency checks) and structure-oriented behavior tests (as feasible model behavior in case of applying extreme values), a behavior pattern test (as matching model predictions with the observed reality) or an empirical confirmation are not available.

Step G: Prioritize measures based on sensitivity analysis. In order to determine the importance of measures, the effect of a parameter change of +/–10% on the top key measure *price* is simulated.

Figure 3-22 shows the results of this numerical sensitivity analysis for most converter elements (except for period-related converters since the resulting change of *price* was less than 0.1% for all of them). Stock elements are in this case not relevant because they are either already altered in the scenarios (stock *reserves*), start empty with the value "0" (stocks *production*, *usage*, *decommissioning*, and *recycling*) or constitute the top key measure itself (stock *price*). Valve elements and converter elements purely calculated from other converters are excluded. The reason is that in this case a change of +/–10% may be caused by different variations of upstream model elements (see section 3.1.4 for further justifications of this simplification).

As can be seen in Figure 3-22, the change of the top key measure *price* sometimes extremely depends on the chosen scenario. For instance, the parameter *average ratio of new scrap during production* influences the price between up to 16.3% (base case scenario) and not at all (optimistic case scenario). The latter might depend on the fact that the optimistic case scenario defines a lower boundary for the price. Hence, parameter changes have no effect in this scenario (except for very minor variations of 0.1% in case of the parameter *average period to adjust price* (not depicted in Figure 3-22)). Another surprise is the strong deviation between price changes due to positive and negative variations of parameters. While in both previous cases the effect on the top key measure was mostly symmetrically, this time the change in absolute terms varies significantly. Examples are the *average cost per recycled ton*, the *average initial value of ore quality*, the *average operating costs per ton*, and the *average ratio of new scrap during production*. This emphasizes the importance of feasible initial values for the simulation. Else misleading implications for information requirements could be derived. As stated above, period-related measures are irrelevant for all scenarios (and hence not depicted in Figure 3-22). But before denying their relevance completely, one could use these results to examine if some parameters, for example, *period for usage*, turn relevant in certain parameter constellations. If this constellation constitutes a realistic scenario, the respective measure gets valuable in certain cases and might then be included.

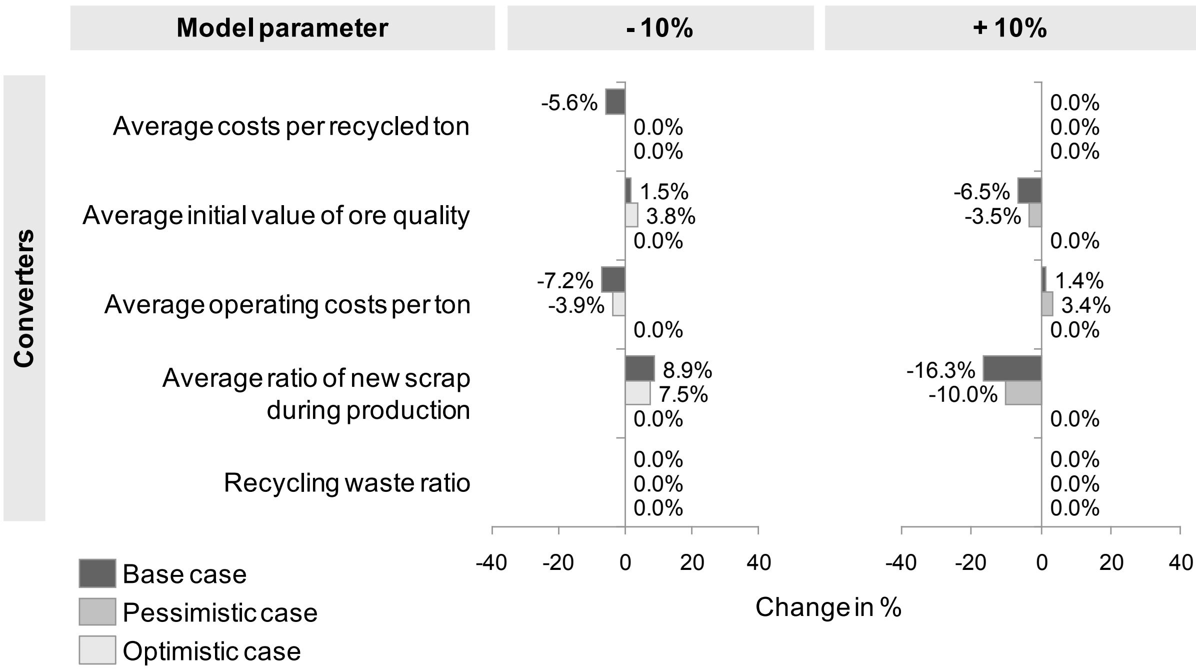

Figure 3-22: Numerical sensitivity analysis of the System Dynamics model for non-renewable resources

For prioritization purposes, as in the first and second case three classes are distinguished: under-proportional (less than 3% change), about proportional (between 3% and 10% change), and over-proportional (more than 10% change) influences on the top key measure. Data availability is selected as second dimension and split into three classes: low (manual or semi-manual data collection), middle (online availability), and high (online availability in high data quality and frequency).

In the example, the company adopts the same prioritization matrix as in the second case (see section 3.2.4): Importance and availability are valued equally. Figure 3-23 shows the resulting matrix for the measures of the model.

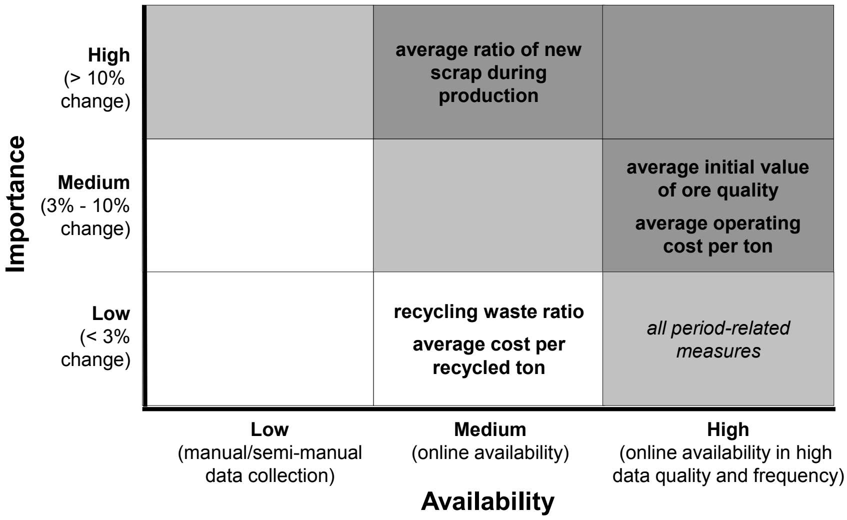

Figure 3-23: Resulting prioritization matrix of the System Dynamics model for non-renewable resources

In this third case, all measures with a high or medium importance also have a high – or at least medium – availability. The importance of *average initial value of ore quality* and *average operating cost per ton* for the development of the *price* is not surprising. Not expected was the very high impact of changes in the *average ratio of new scrap during production* and the low impact of all period-related measures (*average period for production*, *average period for recycling*, *average period for usage*, and *average period to adjust price*).

3.4 Interim Conclusion

In this chapter, three different System Dynamics models were developed and used as cases of application for the proposed I²RDM method for information requirements analysis. While the first two models used CE as top key measure, the last model had no obvious top key measure. The reason for this can be found in the model kind. While an optimization model (the first case of application) inevitably is linked to the company's objectives, both explanation and forecast models not necessarily provide this linkage. In the second case of application, the presented explanation model also linked word-of-mouth effects to the company objective ("maximizing CE") resulting in an easy application of the method. The third case of application however revealed some of the challenges that can occur when using existing System Dynamics models not intended for the I²RDM method: The top key measure and its link to the company's objectives needed to be justified (step A of the method), the area of responsibility appeared rather fuzzy (step B), and the prioritization step had to handle the problems of significant variations between the scenarios (step G). But even with the third model designed as a forecast model for a different purpose (knowledge management), the I²RDM method still could be successfully applied. All steps of the procedure model (see Figure 2-1) could be adopted and the general order of steps proved its usefulness. Thus, the I²RDM method can be considered feasible to improve the role-specific measure-based information-state of decision makers.

But although the method's applicability could be successfully demonstrated, a number of limitations became obvious that leave room for further improvements.

First, the general limitations stated in section 2.5 (i.e., the required effort to build System Dynamics models, the limited applicability to operational and repetitive problems, and the fact that models imply abstracting and simplifying the real world) are inherent to the suggested I²RDM method and cannot be avoided. Although the effort required creating a System Dynamics model can be justified if the model is used for other purposes (such as optimization, explanation, or forecasting in the above described cases), a cost/benefit analysis of building System Dynamics models solely to derive information requirements turns out negative.

Second, the problem remains that information requirements can only be prioritized once a very good understanding of the interrelationships is available. This seems similar to the popular paradox stated by Arrow (1962, p. 615) that "its value [for the decision maker] is not known until he has the information". In this case, the question must be allowed if the value provided by the I²RDM method justifies its costs. But even if the value proposition for practitioners might be limited, it is not without merits for researchers. Information requirements can now be justified and prioritized by. (Subjective) information requirements in the real-world and (objective) information requirements predicted by System Dynamics models can be compared, differences should be analyzed, and implications for improvements might be derived.

Thirdly, the I²RDM method itself leaves room for improvements. The main problem seems to be that the sensitivity analysis relies on a simple ceteris paribus consideration only. While this is a necessary simplification to prevent combinatorial explosion of simulations, it might hide effects occurring in case of simultaneous events changing many measures at the same time. Especially the last case of application (see section 3.3.4) revealed big deviations for some parameters in the examined scenarios due to different starting parameters. This significantly impacts the results of the prioritization. Thus the question how to properly tackle this issue should be addressed by future research.

Fourthly, the I²RDM method shares a shortcoming with many other demand-driven methods for information requirements analysis. The exclusive focus on decision maker's requirements neglects the existing information supply in companies – of which it is reasonable to assume that it is not without relevance. Of course, the initially stated pitfalls as the danger of information overload (see section 2.2) hold true and need to be carefully considered.

This last limitation is addressed in the next chapter that proposes an extension suitable to not only the I²RDM method but also other methods for information requirements analysis.

4 Supply-based Extension of Information Requirements Analysis Methods to Leverage Existing Information Using Metadata[10]

Ensuring adequate information provision continues to be a key challenge of corporate decision making and the usage of Business Intelligence systems. As a matter of fact, the situation becomes increasingly paradox: Whereas decision makers struggle to specify their information requirements and spend much time on obtaining the information they believe to require, the amount of information supplied by Business Intelligence systems grows at a speed that makes it hard to keep track. Thus, it is very likely that the required information or suitable alternatives are available, but neither found nor used. Instead, manual searching causes considerable opportunity cost. Existing approaches to information requirements analysis pay attention to incorporate information supply, but do not provide means for leveraging it in a systematic and IT-supported manner. Hence, this chapter proposes a metadata-based extension for existing information requirements methods consisting of a procedure model and formalism that help identify a suitable subset of the information supplied by an existing Business Intelligence system. The formalism is specified using set theory and first-order logic to provide a general foundation that may be integrated into different conceptual modelling approaches.

This chapter aims at improving the individual measure-based information state of decision makers. In line with the research objective, the information supply is restricted to information of existing Business Intelligence systems stored in data warehouses or data marts. Nevertheless, it is acknowledged that in general information requirements cannot be fully satisfied by the content of existing Business Intelligence systems. It needs to be complemented by qualitative and external information such as rumors, press releases, or external reports of competitors which are out of scope of the following considerations.

The chapter is organized as follows: After the motivation of the problem setting (section 4.1), section 4.2 provides the theoretical background. Section 4.3 proposes the procedure model and the metadata-based formalism. In section 4.4, a short demonstration example illustrates how the approach can be applied in principle. The chapter concludes in section 4.5 with a critical reflection and outlook.

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[10] Chapter 4 was written in collaboration with Dr. Maximilian Röglinger (FIM Research Center) and is a significantly extended version of Mosig and Röglinger (2012).

4.1 Problem Setting

A particular problem in recent times is that the convenient access to Business Intelligence systems and the high storage capacity of underlying data warehouses entice companies into accumulating large amounts of information (Oppenheim 1997). As Business Intelligence systems are historically grown and have been subject to uncontrolled growth in many organizations, it is hard to keep track with the information they supply. Academics approvingly report that “not missing information [is] the primary problem” and that “all information is available somewhere” (Winter and Strauch 2003, p. 237) in most companies. Moreover, practitioners complain about “having great difficulty navigating a rapidly expanding sea of information” (Accenture 2007) and assign high priority to “making better use of information” (Luftman et al. 2009). Against this backdrop, it is very likely that the required information or suitable alternatives are available within an organization, but neither found nor used. The potential of existing information supply to satisfy information requirements is not sufficiently tapped (Winter and Strauch 2003). Instead, decision makers spend much time on obtaining the information they believe to require and thus cause considerable opportunity cost (Axson 2010).

Literature contains numerous approaches dedicated to the elicitation and specification of information requirements particularly for the development of data warehouses and Business Intelligence systems (Giorgini et al. 2008; Kimball et al. 2008; Volonino and Watson 1991; Watson and Frolick 1993; Wetherbe 1991; Winter and Strauch 2004). Apart from few exceptions, the proposed approaches pay attention to incorporating existing information supply. For example, Winter and Strauch (2004) recommend creating an inventory and an information map based on frequently used reports and data schemas. Giorgini et al. (2008) focus on operational application systems and compile the elements of existing source systems into a conceptual data model. Kimball et al. (2008) recommend analyzing existing reports and conducting data audit interviews related to existing operational application systems. The approaches share several characteristics: First, most activities related to leveraging existing information supply require manual effort and are hardly IT-supported. Second, the approaches center on informal or semi-formal concepts, which makes it difficult to cover large amounts of existing information supply systematically. Third, some approaches deal with the initial development of a data warehouse or Business Intelligence system and thus focus on the information supply of operational information systems. Fourth, the approaches provide no explicit means for coping with decision makers’ struggles when specifying information requirements. Despite the value of the presented approaches, there is a need for additional support to leverage the information supply of existing Business Intelligence systems.

This chapter addresses this need by proposing a metadata-based approach consisting of a procedure model and formalism that complement methods for information requirements analysis – as the I²RDM method or the approaches discussed above – and help identify a suitable subset of the information supplied by an existing Business Intelligence system. One can rely on metadata because they play an important role in Business Intelligence systems and have the potential to structure large amounts of data (Foshay et al. 2007; Kimball et al. 2008). In line with many other scholars and practitioners, great potential is seen in leveraging metadata for improving the development of Business Intelligence systems and information requirements analysis. The formalism enclosed in the metadata-based approach is specified using set theory and first-order logic to provide a general foundation that may be integrated into different conceptual modelling approaches. Follow an axiomatic and deductive research approach (Meredith et al. 1989), assumptions are explicated in a formal manner. Both the procedure model and the formalism are derived on this foundation.

4.2 Theoretical Background

When proposing procedure model and a metadata-based formalism for leveraging the information supply of existing Business Intelligence systems, the literature on metadata and multi-dimensional data modeling provides sensible background.

Metadata is commonly characterized as “data about data”. A more operational definition stems from Dempsey and Heery (1998, p. 149) according to whom “metadata is data associated with objects which relieves their potential users of having full advance knowledge of their existence or characteristics“. Metadata is reckoned the DNA of data warehouses and Business Intelligence systems as it defines the elements of these systems and their interrelations (Kimball et al. 2008). Depending on the intended user group, technical and business metadata can be distinguished (Marco 2000). Technical metadata takes on an IT-focused perspective and deals with tables, fields, data types, schedules, distribution lists, and user security rights. Business metadata helps users better understand the content of a data warehouse or Business Intelligence system. It splits into definitional, data quality, navigational, process, audit, usage, and annotational metadata. Here, the focus lies on business metadata.

As for multi-dimensional data modeling, Romero and Abelló (2009) recently published an extensive review of existing approaches. Other insightful resources are Inmon (2009) and Kimball et al. (2008). For the following research, the particularities of specific modeling approaches are of much less interest than the core elements they build on. There is broad consensus that multidimensionality is based on the fact/dimension dichotomy (Romero and Abelló 2009). Dimensions capture different perspectives of analysis and help answer questions related to “who”, “where”, “when”, “what”, or “how”. Typical dimensions are time, location, and product. Dimensions comprise multiple hierarchic levels that allow for changing the degree of aggregation on which analyses are conducted. The dimension time, for example, may comprise levels such as day, week, month, quarter, or year. A fact contains measures, as for instance, sales volume or employee satisfaction. Referring to quantities and values, measures help answer questions related to “how many”. Measures and dimensions are the core elements of multi-dimensional schemas.

4.3 Proposition of a Procedure Model and Formalism

The overall objective of the procedure model and the formalism enclosed in the proposed metadata-based extension is to help decision makers identify a subset of the information supplied by an existing Business Intelligence system that fits the decision makers’ individual information requirements and is derived in a systematic and IT-supported manner. Below, first the general setting is elaborated and basic assumptions are made. Subsequently, the procedure model and the formalism are derived.

4.3.1 General Setting

The unit of analysis is a single historically grown Business Intelligence system that is based on a data warehouse as informational infrastructure. The data warehouse is based on a multi-dimensional data schema whose core elements on schema level are measures and dimensions (Romero and Abelló 2009). All dimensions are treated as orthogonal; it is abstract from structural abnormalities such as parallel hierarchies (Kimball et al. 2008). While an examination on the schema level is reasonable in the context of conceptual modeling, information requirements analysis extends to the instance level because information requirements typically relate to the actual values of measures and hierarchic levels. It is assumed:

(A.1) The multi-dimensional data schema consists of measures $M = \{m_1, m_2, \ldots, m_n\}$ and dimensions $D = \{D_1, D_2, \ldots, D_m\}$. Each dimension includes hierarchic levels $D_i = \{d_{i1}, d_{i2}, \ldots, d_{ip_i}\}$ $(1 \le i \le m)$ where d_{ip_i} and d_{i1} represent the least and the most aggregated level respectively. The information supply on schema level is denoted by $I^{supply} = M \times D_1 \times \ldots \times D_m$.

(A.2) Each hierarchic level d_{ij} $(1 \le i \le m,\ 1 \le j \le d_{ip_i})$ takes values of the domain $dom(d_{ij})$. Each measure m_p $(1 \le p \le n)$ takes values of $dom(m_p) = \mathbb{R}$.

To incorporate metadata into the procedure model and the formalism, information requirements need to be split into two parts where the first part includes requirements that directly relate to the core elements of the multi-dimensional data schema and the second part comprises requirements that relate to meta-attributes (see Table 4-1).

Table 4-1: Considered components of the information requirements

	Related to the core elements of the multi-dimensional data schema	**Related to additional meta-attributes**
Schema level	• Requirements regarding measures • Requirements regarding dimensions • Requirements regarding hierarchic levels	
Instance level	• Requirements regarding the domain of selected measures • Requirements regarding the domain of selected hierarchic levels	• Requirements regarding the value of a meta-attribute <u>for each single</u> selected measure • Requirements regarding the value of a meta-attribute <u>for all</u> selected measures

The first part of the information requirements helps specify requirements where the decision makers know precisely which combinations of measures and dimensions they need. These requirements can be elicited using the existing approaches for information requirements analysis. Although the metadata-based requirements are the more interesting part of this extension, it is necessary to specify also the requirements related to the core elements of the multi-dimensional data schema in a formal manner such that the entire information requirements can be processed simultaneously in an IT-supported manner. Moreover, this helps identify whether requirements related to meta-attributes are fulfilled by previously selected elements of the multi-dimensional data schema. As known from conceptual modeling, there is a dependency between requirements on schema level and on instance level. That is, requirements regarding the instance level of measures or hierarchic levels relate to the domains of the measures or hierarchic levels selected on schema level. Suppose a decision maker needed the measures ‘revenue’ and ‘distribution costs’. While s/he may need the dimensions ‘time’ and ‘place’ for revenues, s/he may require the dimensions ‘time’ and ‘product’ for distribution costs. Regarding revenues, only the hierarchic levels ‘day’, ‘month’, and ‘year’ of the dimension ‘time’ and ‘branch’, ‘region’, and ‘country’ may be required. Furthermore, s/he may only be interested in revenue values above $20,000.

Requirements belonging to the second part of the information requirements relate to additional meta-attributes. The special thing about using meta-attributes is that usually multiple subsets of the information supply exist that meet the related requirements. The reason is that not particular combinations of measures and dimensions have to be specified, but requirements regarding the values of meta-attributes have to be met. Requirements can be defined at two distinct reference levels (see Table 4-2). Either each single selected measure has to fulfill a requirement individually (reference level: each single measure) or all selected measures together have to fulfill a requirement (reference level: all measures). For example, a decision maker might need measures where each single measure is a leading indicator and relates to the Balanced Scorecard (BSC) perspective 'processes' (meta-attributes: 'time horizon' and 'BSC perspective'). Moreover, the collection effort of all selected measures must not exceed a defined limit (meta-attribute: 'collection effort'). It is assumed:

(A.3) Each measure $m_i \in M$ features the same meta-attributes $A = \{a_1, a_2, \ldots, a_r\}$. Each meta-attribute a_q ($1 \leq q \leq r$) takes values of the domain $dom(a_q)$. Meta-attributes are only assigned to measures.

(A.4) The information requirements $I^{req} = \{F^{model,schema}, F^{model,instance}, F^{meta}\}$ comprise requirements related to core elements of the multi-dimensional data schema on schema level, $F^{model,schema} = f_1^{model,schema} \wedge \ldots \wedge f_s^{model,schema}$, requirements related to the core elements of the multi-dimensional data schema on instance level $F^{model,instance} = f_1^{model,instance} \wedge \ldots \wedge f_t^{model,instance}$, and requirements related to meta-attributes $F^{meta} = f_1^{meta} \wedge \ldots \wedge f_u^{meta}$. All requirements are specified in first-order logic. $F^{model,schema}$ only contains requirements that can be covered by the information supply.

(A.5) The subset of I^{supply} that meets all requirements related to the core elements of the multi-dimensional data schema on schema level ($F^{model,schema}$ = T) is denoted by $I^{selected,model,schema}$. The subsets of I^{supply} that meet all requirements related to meta-attributes (F^{meta} = T) are denoted as set family $(I^{selected,meta})_v$ where V is an index set, $|V|$ is the number of different sets, and $v \in V$.

Due to the logical AND operator ($\wedge$) in (A.4), $F^{model,schema}$, $F^{model,instance}$, and F^{meta} only evaluate to *true* (T) if all respective requirements are met. Each of the v set unions $I^{selected,model,schema} \cup (I^{selected,meta})_v$ – subsequently referred to as I_v – is a feasible alternative containing the required information on schema level. $F^{model,instance}$ has not been considered so far as the enclosed requirements can partly be formulated after one of the I_v has been selected. In order to determine which of the I_v should be selected, it is assumed that the decision makers assess the utility and disutility of each alternative.

(A.6) Decision makers strive to maximize the net benefit they receive from the selected subset of the information supply. Each measure $m_p \in \{m_z | \exists(m_z, \dots) \in \bigcup_{v \in V} I_v\}$ that occurs in at least one I_v has a subjectively assigned utility value $u(m_p) \in \mathbb{R}$ and disutility value $d(m_p) \in \mathbb{R}$. The utility and disutility values of a particular subset of the information supply I_v are calculated as follows:
$U(I_v) = \sum_{m_p \in \{m_z | \exists(m_z, \dots) \in I_v\}} u(m_p)$ and $D(I_v) = \sum_{m_p \in \{m_z | \exists(m_z, \dots) \in I_v\}} d(m_p)$.
The overall net benefit is calculated as $U^{\text{net}}(I_v) = U(I_v) - D(I_v)$.

Finally, the way decision makers specify their information requirements needs to be known. Based on experience from related industry projects, it is assumed:

(A.7) Decision makers base their information requirements primarily on measures. Moreover, decision makers are able to specify information requirements related to the core elements of the multi-dimensional data schema and requirements related to meta-attributes independent of one another.

4.3.2 Procedure Model

Based on the elaborations concerning the general setting, properties of a procedure model for leveraging the information supply of existing Business Intelligence systems can be derived. The overall procedure model is shown in Figure 4-1.

First, the procedure model can start with the simultaneous specification of requirements from $F^{\text{model,schema}}$ regarding measures as well as $F^{\text{meta.}}$ This is because decision makers base their information requirements primarily on measures (see A.7) and meta-attributes are only assigned to measures (see A.3). This results in steps ❶ and ❷ of the procedure model.

Second, the utility and disutility of the selected measures can be assessed directly afterwards as only measures are assessed (see A.6). This results in steps ❸ and ❹ of the procedure model. Due to the interdependency of requirements on schema level and on instance level, the requirements regarding dimensions and hierarchic levels from $F^{\text{model,schema}}$ have to be specified first. After that, $F^{\text{model,instance}}$ can be formulated when it comes to report parameterization. This results in steps ❺ and ❻ of the procedure model. The position of steps ❸ and ❹ is also reasonable because labour-intense effort is reduced as decision makers would otherwise have to assess the (dis-) utility of measures, dimensions, and dimensional hierarchy levels that are not implemented.

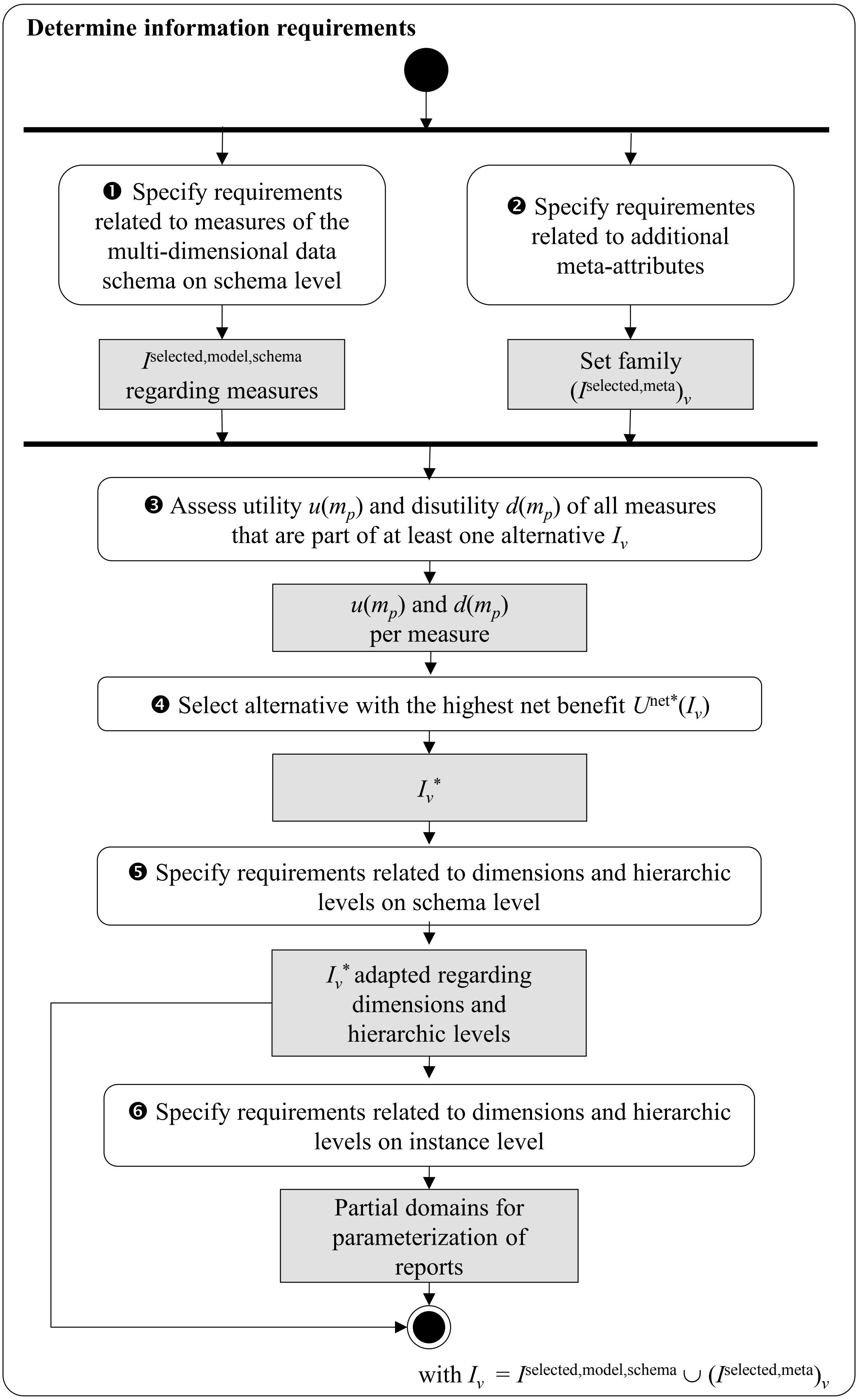

Figure 4-1: Procedure model for leveraging the information supply of existing Business Intelligence systems

4.3.3 Formalization of Information Requirements on Schema Level

Requirements regarding measures

In accordance with this requirement type, $I^{\text{selected,model,schema}}$ may only contain tuples that refer to explicitly needed measures $m_p \in M^{\text{need}}$ ($M^{\text{need}} \subseteq M$).

Formal: $\forall(m_p, \ldots) \in I^{\text{selected,model,schema}}: [m_p \in M^{\text{need}}]$

Requirements regarding dimensions

According to this requirement type, I_v^* (i.e., the subset with the highest net benefit) may only contain tuples whose values for not required dimensions ($D_i \notin D_p^{\text{need}}$) refer to the top hierarchic level ($D_p^{\text{need}} \subseteq D$).

Formal: $\forall(m_p, \ldots, d_{ij}, \ldots) \in I_v^*: [j = 1]$

given: p for a $m_p \in \{m_z \mid \exists\ (m_z, \ldots) \in I_v^*\}$ and i for a $D_i \notin D_p^{\text{need}}$

Requirements regarding hierarchic levels

According to this requirement type, I_v^* may only contain tuples that refer to explicitly needed hierarchic levels D_{pi}^{need} of a dimension $D_i \in D_p^{\text{need}}$ ($D_{pi}^{\text{need}} \subseteq D_i$).

Formal: $\forall(m_p, \ldots, d_{ij}, \ldots) \in I_v^*: [d_{ij} \in D_{pi}^{\text{need}}]$

given: p for a $m_p \in \{m_z \mid \exists\ (m_z, \ldots) \in I_v^*\}$ and i for a $D_i \in D_p^{\text{need}}$

4.3.4 Formalization of Information Requirements on Instance Level

Requirements regarding the domain of selected measures

According to this requirement type, a measure m_p contained in I_v^* may only take values $inst(m_p)$ of an explicitly specified sub-domain $dom(m_p)^{\text{need}}$ ($dom(m_p)^{\text{need}} \subseteq dom(m_p)$).

Formal: $\forall inst(m_p): [inst(m_p) \in dom(m_p)^{\text{need}}]$

given: p for a $m_p \in \{m_z \mid \exists\ (m_z, \ldots) \in I_v^*\}$

Requirements regarding the domain of selected hierarchic levels

According to this requirement type, a hierarchic level d_{ij} may only take values $inst(d_{ij})$ of an explicitly specified sub-domain $dom(d_{ij})^{\text{need}}$ ($dom(d_{ij})^{\text{need}} \subseteq dom(d_{ij})$). In practical application, this must lead to the formation of sub-domains for subordinate dimensional hierarchic levels as well.

Formal: $\forall inst(d_{ij})$: $[inst(d_{ij}) \in dom(d_{ij})^{\text{need}}]$

given: i and j for a $d_{ij} \in \cup_{p,i} D_{pi}^{\text{need}}$

4.3.5 Formalization of Requirements Related to Meta-Attributes

Depending on the scale level of a meta-attribute – i.e., nominal, ordinal, or metric – and depending on the reference level – i.e., each single measure or all selected measures – different operators can be used for comparison, aggregation, or enumeration. Table 4-2 shows the considered operators. Comparisons are based on relational algebra, aggregations and enumerations are based on SQL (Vossen 2008).

Table 4-2: Operators for information requirements related to meta-attributes

Reference level	Operator type	Nominal	Ordinal	Metric
Single measure	Comparison	$\theta_{\text{nom}} \in \{=,\neq\}$	$\theta_{\text{ord}} \in \{<,\leq,=,\geq,>,\neq\}$	$\theta_{\text{met}} \in \{<,\leq,=,\geq,>,\neq\}$
All selected measures	Aggregation	-	-	SUM, AVG
All selected measures	Enumeration	COUNT	COUNT	COUNT

Requirements regarding a single measure

According to this requirement type, only those subsets of I^{supply} are feasible solution sets $(I^{\text{selected,meta}})_v$ where each single measure meets the requirement regarding the value of a specific meta-attribute.

Formal: $\forall m_p$: $[inst(a_q, m_p)\ \theta_{\text{nom|ord|met}}\ x]$

with $m_p \in \{m_z \mid \exists\ (m_z, \ldots) \in (I^{\text{selected,meta}})_v\}$

and $inst(a_q, m_p)$ value of meta-attribute $a_q \in A$ regarding m_p

$\theta_{\text{nom|ord|met}}$ a feasible operator for comparisons

$x \in dom(a_q)$ reference value

Requirements regarding all selected measures (Aggregation: SUM)

According to this requirement type, only those subsets of I^{supply} are feasible solution sets $(I^{\text{selected,meta}})_v$ where the sum of the values of a specific meta-attribute over all selected measures complies with a specific requirement.

Formal: $\sum_{m_p \in Y} inst(a_q, m_p)\, \theta_{\mathrm{met}}\, x$

with $Y = \{m_z \mid \exists\, (m_z, \ldots) \in (I^{\text{selected,meta}})_v\}$

and $inst(a_q, m_p)$ value of meta-attribute $a_q \in A$ regarding m_p

θ_{met} a feasible operator for comparisons on metric scales

$x \in \mathbb{R}$ reference value

Requirements regarding all selected measures (Average: AVG)

According to this requirement type, only those subsets of I^{supply} are feasible solution sets $(I^{\text{selected,meta}})_v$ where the average of the values of a specific meta-attribute for all selected measures complies with a specific requirement.

Formal: $\frac{\sum_{m_p \in Y} inst(a_q, m_p)}{|Y|}\, \theta_{\mathrm{met}}\, x$

with $Y = \{m_z \mid \exists\, (m_z, \ldots) \in (I^{\text{selected,meta}})_v\}$

and $inst(a_q, m_p)$ value of meta-attribute $a_q \in A$ regarding m_p

θ_{met} a feasible operator for comparisons on metric scales

$x \in \mathbb{R}$ reference value

Requirements regarding all selected measures (Enumeration: COUNT)

According to this requirement type, only those subsets of I^{supply} are feasible solution sets $(I^{\text{selected,meta}})_v$ where the number of occurrences of a reference value of a specific meta-attribute complies with a specific requirement (considering all selected measures).

Formal: $|\, Y\, |\ \theta_{\text{met}}\ x$

with $Y = \{m_p \mid [\exists\, (m_p, \ldots) \in (I^{\text{selected,meta}})_v\,] \wedge [inst(a_q, m_p)\ \theta_{\text{nom|ord|met}}\ z]\}$

and $inst(a_q, m_p)$ value of meta-attribute $a_q \in A$ regarding the measure m_p

$\theta_{\text{nom|ord|met}}$ a feasible operator for comparisons

$x \in \mathbb{R}$ reference value (indicating the number of occurrences)

$z \in dom(a_q)$ value of a_q

4.4 Demonstration Example

The following example illustrates how the metadata-based formalism and the procedure model can be applied. It was inspired by a previously conducted industry project. The decision makers under consideration are German sales managers of a production company with its own branch network. The multi-dimensional data schema is depicted in Figure 4-2 as a star schema that follows the typical account model of SAP (SAP n.d.) and is based on the classification scheme with simple hierarchies (Bauer and Günzel 2008).

Following six measures are considered: sales (m_s), distribution costs (m_{dc}), employee satisfaction (m_{es}), estimated demand (m_{ed}), reaction time to requests (m_{rt}), and the number of new customers (m_{nc}). As meta-attributes, the decision makers' possibility to influence a measure (a_I with $dom(a_I)$ = {high, medium, low}), the Balanced Score-card perspective (a_{BSC} with $dom(a_{BSC})$ = {finance, employees, market, processes}), and the time horizon (a_{TH} with dom(a_{TH}) = {leading indicator, lagging indicator}) are considered. The corresponding values are listed in the first four columns of Table **4-3**.

Following the procedure model (see Figure 4-2), the sales managers first specify their information requirements related to the measures of the multi-dimensional data schema on schema level (step ❶). Thereby, traditional approaches to information requirements analysis or the proposed I²RDM method can be applied. In this example, the sales managers require the measure sales (m_s) in any case. In step ❷, a policy of the sales management to have at least two leading indicators is formalized. Furthermore, the chief sales officer requires the sales managers to incorporate one measure of each Balanced Scorecard perspective. This is modeled using four requirements whereby the COUNT operator ensures that exactly one measure is selected for each perspective. Based on this input, the set family of feasible solutions can be generated in an IT-supported manner.

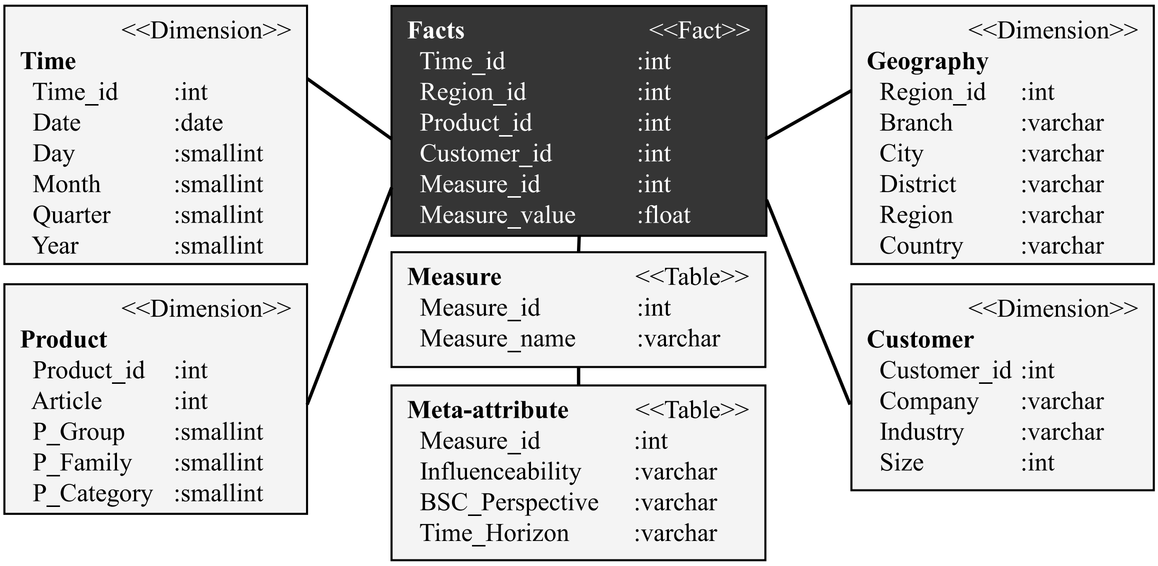

Figure 4-2: Exemplary star schema extended by meta-attributes

Subsequently, each measure contained in at least one feasible solution is presented to the sales managers for utility and disutility assessment (step ❸). Since an exact determination is difficult, utility and disutility categories are used. Utility values range from 0 (“not helpful”) to 5 (“essential information”), whereas disutility values range from 1 (“intuitive and easy to interpret”) to 5 (“hard and time-consuming to understand”). The result of the assessment is depicted in the last three columns of Table 4-3. The utility and disutility values serve as input for step ❹, which automatically selects the alternative with the highest net benefit. Note that even measures with a stand-alone negative net benefit can be part of the optimal alternative. In the example at hand, m_{rt} is selected because it is the only measure that fulfills the requirement to include a measure from the Balanced Scorecard perspective ‘processes’.

In step ❺, irrelevant dimensions or hierarchic levels are excluded. Here, an evaluation based on the customer dimension is not required. In addition, the decision makers do not require fine-grained hierarchic levels such as “Date”, “Day”, “Article”, and “P_Group”. These restrictions apply to all measures, that is, the sales managers do not use the possibility of measure-specific definitions. Requirements on instance level are expressed in the final step ❻ when it comes to the parameterization of reports. Since the sales managers are accountable for Germany, they require only measures where the hierarchic level “Country” has the value “Germany” (or the associated values on subordinate levels).

Table 4-3: Values of meta-attributes and (dis-) utility values for each measure

m_p	a_I	a_{BSC}	a_{TH}	$u(m_p)$	$d(m_p)$	$u(m_p)$-$d(m_p)$
m_s	medium	finance	lagging	5	1	4
m_{ec}	medium	finance	lagging	4	2	2
m_{es}	high	employees	leading	2	2	0
m_{pd}	low	market	leading	4	3	1
m_{rt}	high	processes	lagging	2	3	-1
m_{nc}	medium	market	leading	3	1	2

As a result, that part of the multi-dimensional data schema has been identified that fulfills the information requirements, enables the parameterization of reports based on requirements on instance level, and provides the highest net benefit for the sales managers.

4.5 Interim Conclusion

This chapter dealt with the question on how to improve the individual information state of decision makers in a systematic and IT-supported manner. As complementation of existing methods for information requirements analysis as the proposed I²RDM method, a metadata-based extension was presented that consists of a procedure model and formalism. Using the formalism, all information requirements are specified using set theory and first-order logic, which is an important prerequisite for IT support and the reduction of costly manual work. As the usage of metadata allows for the existence of multiple subsets of the information supply to meet the information requirements, the procedure model also includes a step where the utility (e.g., perceived usefulness) and disutility (e.g., information processing complexity) can be assessed and the optimal subset can be determined. As the feasible subsets can be identified in an IT-supported manner, even large amounts of information supply can be leveraged in a systematic and less costly way. Using metadata also alleviates the problem of having to specify each single combination of required measures and dimensions explicitly.

On the other hand, the proposed approach is beset with limitations that need to be taken into account when applying it in industry settings. Other limitations might motivate future research endeavors:

- Prior to application, appropriate meta-attributes have to be identified and – if not already available – filled with values. While this may be quite costly for a single use case, it is worth the effort in case of repeated applications for multiple groups of decision makers. As Stroh et al. (2011) point out, information requirements analysis is not a one-time project, but a continual process. The proposed formalization based on metadata is a first step in this direction since it enables the realization of meaningful automation potential.
- The approach restricts itself to consider existing information supply – which will in general not fully satisfy a decision maker's information requirements. In this case, the remaining parts of the information requirements have to be covered using existing approaches for information requirements analysis. One might also consider conveying the basic ideas of the presented approach to the elicitation of external information from the Internet.
- Although IT support plays an important role, an implementation is pending. This would shape up useful for practical application and evaluation issues. Moreover, it seems promising to investigate how the proposed formalism can be integrated with conceptual approaches from the area of multi-dimensional data modelling.

- The information requirements are currently treated as constant. While this is approximately appropriate for standard reporting and well-structured problems, it is not always the case in a complex and disruptive business environment. Although requirements based on metadata are a first step to address this issue, a more detailed investigation seems reasonable.

Despite its limitations, the proposed approach is a first step to address the research gap of leveraging the information supply of existing Business Intelligence systems and toward an enhanced usage of metadata in the context of Business Intelligence systems. This chapter presented necessary formal groundwork that may guide future application and research.

5 Conclusion

5.1 Summary

The overarching objective of this dissertation was to present approaches to improve the measure-based information state of decision makers in order to reach goals (see Figure 1-3 in section 1.3). For this purpose, a core-shell model was adopted to distinguish between role-specific and individual information requirements of decision makers.

In chapter 2, the I²RDM method was developed to improve information requirements analysis for Business Intelligence systems by using System Dynamics to identify and prioritize role-specific and measure-based information requirements of decision makers. The presented procedure model drawing from the System Dynamics methodology can help to overcome current shortcomings in information requirements analysis such as, for instance, missing prioritization. The method was evaluated referring to method engineering research and ideas for further development were suggested. Limitations include a missing extensive documentation of terms and meta models, an owing proof of utility in a real-world setting, and a potential need for further implementation principles. (Mosig 2012)

In chapter 3, three different System Dynamics models were developed and used as cases of application for the proposed I²RDM method to demonstrate and evaluate its feasibility:

- The first System Dynamics model proposed an optimization model for determining the optimal payment amount of a complaint solution in the service industry. A value-based perspective was adopted in order to examine the conflict between the loss in value due to defecting customers on the one hand and the loss in value due to exaggerated investments in customer loyalty on the other hand. Simulation results showed that previous approaches do not consider decisive factors. The optimization model was evaluated based on an example from the mobile telecommunication industry. As a result, the model provides new insights for the development of decision support systems. (Meier et al. 2011)
- The second System Dynamics model combined existing scientific findings to an integrated explanation model to simulate economic implications of word-of-mouth (WOM) effects. First, a stable system has been built using an analytical decision model to allocate a fixed promotional budget between acquisition and retention spending. Second, complaint management as the central part of retention efforts was further detailed, referring to both the expectancy-

disconfirmation theory and the exit-voice-loyalty theory. Third, word-of-mouth effects based on four antecedents and three consequences were included. Based on three different scenarios, the implications of parameter changes on the development of a company's value could be examined. The explanation model can serve as hypotheses generator for empirical marketing researcher. Furthermore, it may improve the mental model of decision makers by enabling them to better value the magnitude and possible consequences of word-of-mouth effects. (Mosig et al. 2012)

- The third System Dynamics model aimed at forecasting price developments in order to contribute to knowledge re-use and re-creation for better organizational performance. In the context of the use of non-renewable resources, short- and long-term consequences on demand, supply, and price were uncovered and examined. The resulting forecast model can be seen as an explicitly formalized mental model of one or several experts. The used case of indium showed how externalized and combined real-world information used in scenarios can enable a company to communicate a coherent and comprehensive view for semi-structured or even unstructured strategic decisions. (Gleich et al. 2011)

The I²RDM method was applied to all three System Dynamics models. Thereby, the method could be easily applied to the first two models since Customer Equity as "native" top key measure was already built into the models. Even in the third – admittedly challenging – application, the I²RDM could be successfully adapted to a System Dynamics model without an obvious top key measure that is linked to a company's objectives. Limitations include the need for a very good understanding of the problem domain in advance, the reliance on a purely numerical sensitivity analysis without the consideration of simultaneous parameter changes, and the neglect of the existing information supply within a company.

Chapter 4 addressed the issue of how to improve the individual measure-based information state of decision makers in a systematic and IT-supported manner. As complementation for existing demand-driven information requirements analysis approaches – such as the proposed I²RDM method – a supply-driven metadata-based extension was presented that consists of a procedure model and formalism. The information requirements were split into requirements that relate to elements of a multi-dimensional data schema and those that relate to meta-attributes. Using the formalism, all information requirements are specified using set theory and first-order logic, which is an important prerequisite for IT support and the reduction of costly manual work. As the usage of metadata allows for the existence of multiple subsets of the information supply to meet the information requirements, the procedure model also includes a step where the utility (e.g., perceived usefulness) and disutility (e.g., information processing complexity) can be assessed and the optimal subset can be determined. As the feasible subsets can be identified in an IT-supported manner, even large amounts of information supply can be leveraged in a systematic and less costly way. The proposed procedure model was derived from a set of assumptions on the general setting and the decision makers' behaviour. (Mosig and Röglinger 2012)

In conclusion it can be said that the presented I²RDM method and its extension contribute to improving the measure-based information state of decision makers in general and to enhancing the step of information requirements analysis during the design phase of Business Intelligence system implementations in specific. The remaining challenges provide opportunities for future research.

5.2 Outlook

Further research on subjects touched in this dissertation can be divided into following areas: (1) enhancements of the I²RDM method using System Dynamics itself, (2) improvements of the supply-based extension using metadata, and (3) inclusion of data not covered in this dissertation.

Ad (1) enhancements of the I²RDM method using System Dynamics itself:

- The numerical sensitivity analyses – on which the I²RDM method is based – should be improved. On the one hand, an automated calculation of advanced sensitivity analyses could be integrated into simulation tools as Vensim®. Thereby, the ceteris paribus assumption should be relaxed in order to increase external validity. Since the resulting combinatorial explosion of required sensitivity analyses constitutes a serious drawback, one might also consider examining the importance of measures based on the underlying equations of the System Dynamics model. This might be reasonable provided that the respective measure is not part of multiple interlaced causal loops.
- Although the principal feasibility of the I²RDM method could be shown, an application in a real-world setting is missing to prove its usability. From a scientific point of view, a cost/benefit comparison of different methods for information requirements analysis applied in practice would be particular valuable. Thereby, diverse issues need to be solved such as how to ensure comparability across business units (or groups of decision makers) or how to avoid learning and/or memory effects if comparing all methods within the same business unit (or group of decision makers).

Ad (2) improvements of the supply-based extension using metadata:

- A potential enlargement of the presented approach could be to convey the basic idea to elicit structured external information from the Internet. Content of web pages structured in Extensible Markup Languages (XML) can be parsed and “understood” by applications in an automated manner. The idea to include external data, for instance from the Internet, in Business Intelligence systems is not new (see Meier 2000) but a implementable procedure including a machine-translatable formalism, e.g., by using set theory and first-order logic, seems to be missing.
- Another shortcoming that should be overcome is the static view whereby information requirements are treated as constant. Nowadays, often complex and disruptive business environments require a flexibility exceeding the potential of metadata usage. Thus, leaving the purely syntactic level and including semantic based concepts, as for instance proposed by ontologies, might be a fruitful area of future research endeavors.
- Once again, an application in a real-world setting is missing. A proof-of-concept by implementing a prototype in a test or training Business Intelligence system seems to be a reasonable and achievable goal. The inclusion of this prototype into existing Business Intelligence systems on the market – enabling further insights on the use of metadata to structure the growing information amount based on empirical evaluations and field experiments – would probably prove more challenging.

Ad (3) inclusion of data not covered in this dissertation to improve the information state of decision makers in order to reach goals:

- The work presented omitted general information needs as depicted in the core-shell model (see Figure 1-2). Admittedly, it is challenging to define a common core of information requirements of all decision makers within a company beyond rather obvious facts such as information on the current financial and operational status of the company, major industry trends, the state of the overall economy, or cross-departmental legal changes. Despite this challenge, improvements would affect all decision makers equally. Hence even a small benefit would be leveraged significantly, potentially justifying the effort of even small contributions.
- The inclusion of semi-structured or even unstructured data could also prove a fruitful research area. It is acknowledged that in general structured (measure-based) information requirements need to be complemented by qualitative and/or external information such as rumors, press releases, or external reports of competitors. Since especially semi-structured and unstructured data ac-

count for the biggest share of growing data volume (Dambeck 2012), there is need for improvements in this area, too. Since System Dynamics research already includes approaches on how to incorporate qualitative data into models (Marjaie and Rathod 2011), the proposed I²RDM method might also be extendable in this direction.

These and other future research efforts are required to fence the initially described information proliferation and to channel and aggregate the observable data explosion towards value-adding information provisioning that actually improves the information state of decision makers. Only then, the opportunities of the newly emerging “data treasures” can outweigh the threat of making matters worse by drowning decision makers in increasing information overload that ultimately might result in a loss of company value.

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